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Multiclass Damage Detection for Autonomous Post-disaster Reconnaissance Using Quantum Convolutional Neural Network

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Abstract. Timely assessment of earthquake-induced building damage is critical for ensuring life safety, mitigating financial losses, expediting the rehabilitation process, and improving structural resilience. Due to the exponential growth in computer power and intrinsic capacity to address problems with manual inspections, the use of artificial intelligence (AI) in post-earthquake inspections and reconnaissance has drawn a lot of attention in recent years. With recent advancements in non-contact sensing technologies such as cameras, unmanned aerial and ground vehicles, the structural health monitoring (SHM) community has seen a significant increase in deep learning-based condition assessment methodologies of structural system. These deep learning algorithms mostly rely on convolutional neural networks (CNNs), which has risen its popularity for many machines learning (ML) applications, particularly in the field of image recognition. However, machine learning algorithms experience computational bottlenecks due to the curse of dimensionality. This study presents the adoption of Quantum Convolutional Neural Network (QCNN) to classify the building damages into five damage grades (1) Negligible to slight damage (2) Moderate damage (3) Heavy damage (4) Very heavy damage and (5) Collapse. The reinforced concrete building damage images collected from past-earthquake events are used to train the models and their performance is evaluated based on the testing images, neither of which are included to the training dataset. Furthermore, the comparison is made between the results obtained from QCNN and various CNNs architectures.

Keywords: damage detection · convolutional neural network · quantum convolutional neural network · earthquake damage images

1 Introduction

Most of the cities around the world are evolving into integrated systems with dense populations and structures. Buildings are the most common structure available in the built environment. Therefore, there requires an accurate and efficient assessment of buildings' damage after the earthquake for post-disaster structural recovery and reconstruction. On the occurrence of an unexpected event like earthquake, people are homeless because of two reasons: (1) very severe, partial, or total collapse of the building structures and (2)

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due to lack of untimely or rapid seismic damage assessment of the building structures. For the second reason, a methodology is required to carry out the rapid damage assessment of numerous buildings after the earthquake which suggests us whether the building can be safely used immediately after the earthquake by realizing the probability of damage levels. Furthermore, the information about the damage condition of buildings after the earthquake are crucial for decision makers and stake holders to implement the disaster risk reduction strategies and to respond systematically in post-disaster situation.

The tradition visual inspection method requires the mobilization of well-trained professionals immediately after the earthquake, therefore there may be insufficiency of these experts to be mobilized to the affected areas at the same time. Most importantly, the safety of the inspector cannot be guaranteed in that aftermath of the earthquake. The available time may be limited to collect the buildings information in more detail where there is chance of missing some important damage information which could led negative results. Due to increase in computation power, the use of artificial intelligence (AI) has increased significantly in predicting the seismic damage of the building structures. The deep learning techniques, especially Convolutional Neural Network (CNN) has used widely for classification purposes in image recognition and object detection. Several studies [1–3] examined the feasibility of employing CNN for effective and autonomous identification of various structural damage. Ghosh et al. [4] implemented region-based CNN (Faster RCNN) to identify different buildings' damages such as surface crack, spalling, spalling with exposed rebars and severely buckled rebars. Cha et al. [5] used CNN to detect concrete crack using different lightening conditions. Yeum et. al [6] demonstrated the CNN techniques and its capabilities to classify collapse or non-collapse buildings and to detect spalling in concrete structures using images collected from past earthquake events. Ghosh et al. [4] used region-based CNN (Faster RCNN) to detect different buildings' damages such as surface crack, spalling, spalling with exposed rebars and severely buckled rebars.

Recently, the adoption of Quantum Convolutional Neural Network (QCNN) has increased in image classification. A computing environment that is different from conventional computers is provided through the use of quantum computers. Superposition and entanglement, which are not present in classical computing environments, can be used by quantum computers in particular to achieve high performance through parallelism amongst qubits [7]. This enables the use of quantum machine learning when datasets grow exponentially and are difficult to solve by the classical machine learning models. In this study, the capability of QCNN is investigated to predict the multi-class RC buildings' damages using the buildings' damage images collected from past-earthquake events. Furthermore, the comparison is made between the prediction results obtained from QCNN and various CNNs architectures.

2 Overview of the Proposed Method

In this study, the multiclass damage detection of RC buildings after the earthquake using Quantum Convolutional Neural Network (QCNN) is presented. The RC buildings' damage images are downloaded from datacenterhub.org (2015 Nepal earthquake), damage reports and online available in google for past-earthquakes events occurred across the world (2011 Great East Japan earthquake, 2017 Juchitan, Mexico earthquake, 2008 and 2022 Sichuan, China earthquake, 2010 Chile earthquake, 2010 Haiti earthquake, etc.). These images are classified into five different damage grades (1) Damage grade 0 (DG0): Negligible to slight damage (2) Damage grade 1 (DG1): Moderate damage (3) Damage grade 2 (DG2): Heavy damage (4) Damage grade 3 (DG3): Very heavy damage and (5) Damage grade 4 (DG4): Collapse following EMS-98 [8] guidelines as explained in Table 1. These images are utilized to train the QCNN and CNN models. The performance of the QCNN and CNN are evaluated based on the testing RC buildings' damage images, neither of which are included to train the model. Furthermore, the confusion matric parameters such as precision, recall and f1-score are calculated. In this study a total of 2103 damage images are considered out of which 2053 are used for training purpose and 60 are used for the testing purpose as shown in Fig. 1.

Table 1. Classification of damage images into five grades

Damage grade	Damage image	Descriptions
Grade 0		- Hair line cracks on plaster - Fall of small piece of plaster
Grade 1		- Crack in many walls - Fall of plaster in larger area - Damage to non-structural parts
Grade 2		- Large and extensive crack in most walls - Failure of non-structural element - Significant structural repair is required
Grade 3		- Large gap occurs in wall - Wall collapse - Partial structural failure of slab/roof - Building takes a dangerous state
Grade 4		- Total or near collapse of building

3 QCNN: An Extension of CNN for Image Classification Using Quantum Convolutional Filter

CNN is one of the deep learning algorithms and models that have made an effect in the field of AI and machine learning. It is widely adopted for classification purposes in image recognition and object detection. It is made up of numerous layers of filters

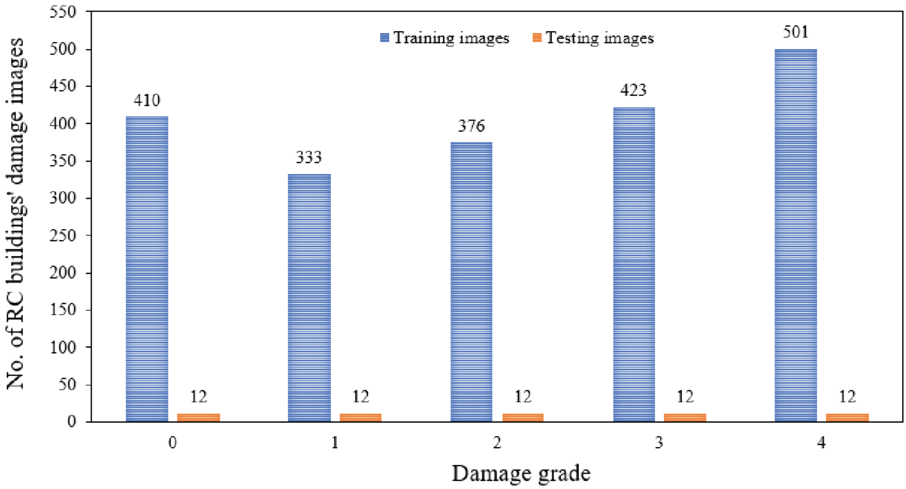


Fig. 1. Number of training and testing images of each damage grades

that are used to generate feature maps from input data, the most important of which is the convolutional layer, hence the term Convolutional neural networks. The general structure of CNN is explained in Fig. 2. In CNN, generally an input array is applied with alternating convolutional layers (with an activation function) and pooling layers and some fully connected layers before the output.

In this study, we use the Quantum Convolutional Neural Network, a quantum machine learning model originally proposed by Henderson et al. [9]. QCNN are just an expansion of traditional CNN that include an additional transformational layer known as the quantum convolutional layer as shown in Fig. 3a. The key difference is that in CNN, the convolutional filters (also known as kernel) present in the convolutional layers extracts features from the input images performing dot products of matrix between the sub-region of input image and kernel as shown in Fig. 2b, whereas in QNN, quantum convolutional

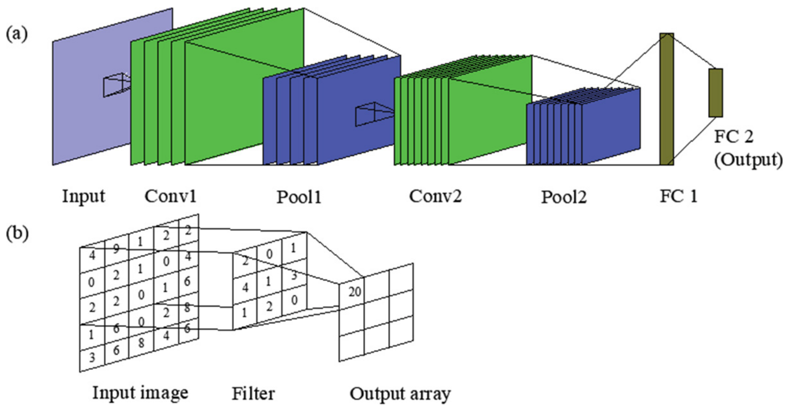


Fig. 2. General architecture of CNN

filters utilize the random quantum circuit, which takes as input spatially local subsections of images from the dataset as explained in Fig. 3b. The qubits are initialized with the pixel data corresponding to the filter size in the encoding process and the decoding process yields new classical data after measurement. This process is repeated to complete the new feature map.

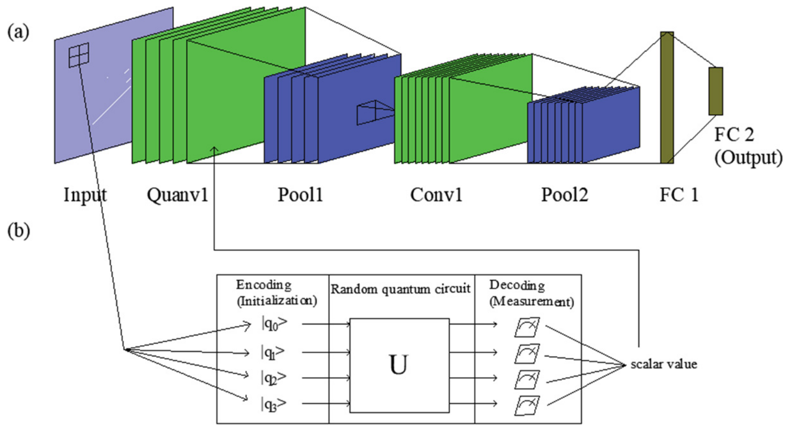
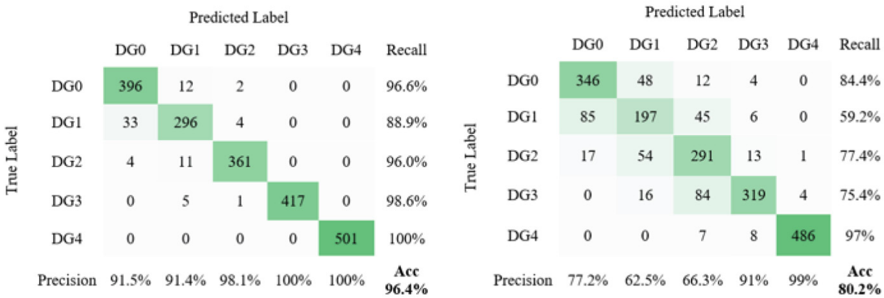


Fig. 3. Quantum convolutional neural networks

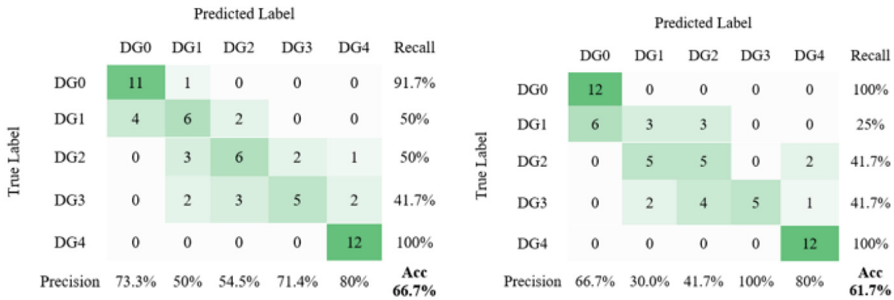
4 Performance of QCNN and CNN Model

In this study, the simple architecture adopted for QCNN, and CNN model consists of two convolutional layers with 64 kernels of size 3 and relu activation function, two MaxPooling layers after each convolutional layer, a flatten layer and a dense layer with SoftMax function before the output. Figure 4 shows the confusion matrix of QCNN and CNN models on the training images. It is observed that the overall damage grade prediction accuracy in QCNN is 96.4% which is higher than in CNN i.e., 80.2% on the training images. Furthermore, precision and recall values are also higher in QCNN than in CNN. The performance of this trained models is evaluated based on the predicting capability of the damage grade of test images and the confusion matrix on the testing images are shown in Fig. 5. It illustrates that the QCNN model can predict the damage grade of testing images with higher accuracy of 66.7% than CNN of 61.7%. Although CNN has 100% recall on DG0 the recall value for other damage grades is found higher in the case of QCNN. Table 2 shows that the f1-score, which is the geometric mean of precision and recall, is found higher in the case of QCNN than CNN in both training and testing images (except DG3).



(a) (b)

Fig. 4. Confusion matrix on training images (a) QCNN (b) CNN



(a) (b)

Fig. 5. Confusion matrix on testing images (a) QCNN (b) CNN

Table 2. f1-score of CNN and QCNN on training dataset

Damage Grade	Training images			Testing images		
	CNN	QCNN	Images	CNN	QCNN	Images
DG0	0.80	0.94	410	0.80	0.81	12
DG1	0.60	0.90	333	0.27	0.50	12
DG2	0.71	0.97	376	0.41	0.52	12
DG3	0.82	0.99	423	0.58	0.52	12
DG4	0.98	1.00	501	0.88	0.88	12

5 Comparison with Various CNN Architectures

Various CNN architectures such as AlexNet, VGG16, VGG19, ResNet50 and InceptionV2 are trained on the same training images adopted in the above section for CNN and QCNN model and their capabilities on predicting damage grade are compared based on the same testing images. Table 3 summarize the overall accuracy obtained from adopting different CNN models on testing images. It shows that the overall accuracy obtained from QCNN model is higher than other CNN architectures.

Table 3. Summary of prediction results

Various CNN architecture						
CNN	QCNN	Alex Net	VGG16	VGG19	ResNet50	InceptionV2
61.7%	66.7%	50.0%	53.3%	58.3%	51.6%	60.0%

6 Conclusion

This study primarily investigates the effectiveness of using QCNN to classify RC buildings' damages after the earthquake. For this purpose, the earthquake damage images collected from various source are utilized to train the model. The higher accuracy, precision, recall and f1-score calculated using the confusion matrix on training and testing images suggest that the QCNN model is better than the CNN model. Furthermore, the QCNN prediction accuracy is compared with widely used CNN architecture such as AlexNet, VGG16, VGG19, ResNet50 and InceptionV2. It is found that the overall prediction accuracy obtained from QCNN model is higher than other CNN architectures adopted in this study.

However, the number of earthquake damage images need to be increased further to obtain the higher prediction accuracy on the testing images. In this study only RC building damage images are considered which can be extended to predict the seismic damage of wooden building, steel building, etc. This study is focused only on the simulation at the moment however developing hardware such as iPhone or unmanned ariel vehicle (UAV) where the QCNN model can be integrated can help in predicting rapid multiclass damage detection of buildings after the earthquake.

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