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An Evaluation of FRQI and NEQR Encoding Using QCNN for Forecasting Tropical Cyclone Intensity

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Abstract. Effective weather forecasting for cyclones is crucial for minimizing harm to both people and the environment. Accurate estimation of tropical cyclone (TC) intensity is essential for disaster prevention. Although convolutional neural networks (CNNs) have improved this process, they often struggle to capture global spatial relationships in images. Quantum Image Processing (QIP) leverages quantum computing advantages but faces challenges such as noise and hardware limitations. This study represents the first effort to estimate tropical cyclone intensity prediction using two popular quantum image representation formats: Flexible Representation of Quantum Images (FRQI) and a Novel Enhanced Quantum Representation (NEQR), as data encoders in Quantum Convolutional Neural Networks (QCNN) utilizing INSAT 3D satellite images. By employing TCs from 2012 to 2021 as training data, the model achieved an overall mean square error (MSE) of 0.0384 for FRQI and 0.0002 for NEQR. The findings indicate that NEQR significantly outperforms FRQI in cyclone image prediction.

Keywords. Tropical cyclone, intensity prediction, QCNN, NEQR, FRQI.

1 Introduction

In recent years, the devastating impact of tropical cyclones on human life, property, the economy, agriculture, and development has highlighted the urgent need for accurate and efficient methods of estimating cyclone intensity [1].

Quantum image processing (QIP) combines quantum computing with traditional image processing techniques to enhance the management and interpretation of high-dimensional image data. Traditional methods often struggle with high computational costs and slow processing speeds when handling large datasets. Quantum computing improves efficiency by utilizing superposition and entanglement for parallel analysis [2].

Key techniques such as Quantum Image Representation (QIR), Flexible Representation of Quantum Images (FRQI), and Novel Enhanced Quantum Representation (NEQR) enable the encoding of traditional images to be encoded into quantum formats, enhancing feature extraction and manipulation [3]. Quantum algorithms, including Grover's search and the quantum Fourier transform, significantly accelerate tasks such as image recognition, compression, and pattern matching, offering exponential speedups compared to classical methods.

However, the adoption of QIP faces challenges like noise, decoherence, and quantum hardware limitations. Hybrid quantum-classical approaches may provide solutions for practical applications in fields such as autonomous systems, medical imaging, and satellite data analysis. Yella Krishna et al [1] proposed a CNN algorithm for estimating the intensity of cyclones. Their approach combines features from satellite images and grayscale data, resulting in a more precise prediction model. This enhanced predictive capability strengthens early warning systems and provides a more effective means of mitigating the adverse effects of cyclones. Rose Atuah et al [2] used various deep learning models such as CNN, LSTM, and CNN-LSTM for tropical cyclone intensity prediction using Hursat and Bestrack datasets from the NOAA. This study focuses on the superior performance of the LSTM model and underscores the potential of these methods to improve forecast accuracy. Biao Tong et al [3] investigated tropical cyclone(tc) intensity estimation using satellite cloud images, leveraging advanced deep learning techniques and smoothing methods. The study compared one-stage and two-stage strategies, finding that a hybrid approach combining both, along with smoothing techniques, achieved superior accuracy than most existing models. Chong Wang et al [4] proposed a new deep learning framework known as TCIF-fusion, designed to enhance tropical cyclone intensity predictions in the Northwest Pacific region. This approach is guided by model-based knowledge and utilizes a comprehensive dataset of 20,533 samples. The dataset incorporates ERA5 reanalysis data, satellite infrared (IR) imagery, and multiple other factors.

Their method achieved a 24-hour forecast error of 3.56 m/s, outperforming traditional and advanced DL models by 4–22%. Juhyun Lee et al [5] developed a hybrid-CNN model combining satellite data and numerical model outputs to forecast TC intensity with lead times of 24, 48, and 72 hours. The model showed significant improvements, with skill score gains of 22%, 110%, and 7% for the respective lead times. Xiao-Yan Xu et al [6] designed deep CNN models to predict tropical cyclone intensity, minimum central pressure (MCP), and maximum 2-minute mean wind speed (MWS) near the center. The models utilized data from ocean and atmospheric reanalysis and Best Track hurricane records (2014–2018). Sensitivity experiments were performed to assess the influence of various predictors, revealing that VGG-16 delivered the best results. Daisuke Matsuoka et al [7] introduced a deep learning approach using CNNs to identify tropical cyclones (TCs) and their precursors based on 20 years of simulated OLR data. Their method achieves high detection probabilities (POD 79.9–89.1%) and reasonable false alarm ratios (FAR 32.8–53.4%), successfully identifying precursors up to 7 days before TC formation. None of the existing work indicates the use of different encoding models combined with quantum algorithms for predicting cyclone intensity. Alijoyo et al. (2024) [8] proposed a hybrid CNN-Bi-LSTM model optimized with a GA-enhanced Fruit Fly Optimizer (FFO) for predicting cyclone intensity.

Their approach outperforms traditional models by effectively capturing spatial-temporal patterns, achieving an accuracy of 99.4%, which surpasses that of VGG-16 (78%) and Ty 5-CNN (95.23%).

This model enhances disaster preparedness by providing more accurate forecasts of cyclone intensity. Desale et al. [9] proposed a CNN-based model for estimating cyclone intensity using satellite images. This model incorporates histogram analysis for feature extraction and employs adaptive thresholding techniques (mean, Gaussian, Otsu) for segmentation. Unlike traditional methods, their approach also predicts potential coverage distance and introduces a user-friendly visualization portal, thereby enhancing accessibility for end-users in disaster preparedness and response. Xu et al. [10] proposed a CWGAN-GP-based model for predicting the evolution of tropical cyclone (TC) intensity. This model treats TC intensity as a random variable influenced by both the state of the TC and various environmental factors. Trained on a dataset of 1,010 historical TCs, the model effectively captures high-dimensional, non-Gaussian probabilistic characteristics, outperforming traditional regression models. It separately calibrates TC behaviors over oceanic and terrestrial environments before integrating the

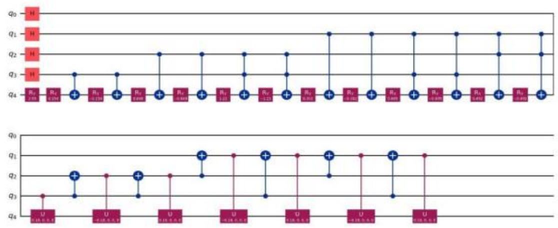

Fig. 1. FRQI- Quantum Circuit

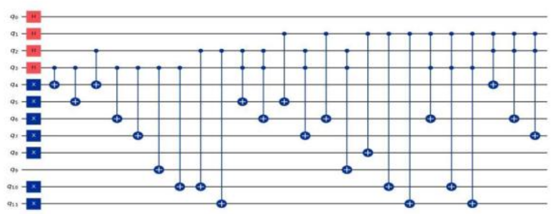

Fig. 2. NEQR-Quantum Circuit

results. The findings demonstrate improved accuracy in replicating probabilistic intensity distributions and input-output relationships, underscoring the model's potential for TC risk assessment and hazard prediction in regions such as Southern China.

Atuah et al. [11] developed three deep learning models (CNN, LSTM, and CNN-LSTM) to predict tropical cyclone (TC) intensity using the Hursat and Bestrack datasets from NOAA. Their findings indicate that while the LSTM model performed the best, the differences in performance among the models were minimal.

This research contributes to enhancing TC intensity prediction, which can help mitigate the devastating effects of cyclones on lives and property. Stein et al. [12] introduced QuCNN, a Quantum Convolutional Neural Network that adapts classical CNNs for quantum systems through entanglement-based backpropagation. This model calculates similarities between quantum filter states and quantum data states, facilitating efficient training with a single-ancilla qubit routine.

Validated on MNIST images, QuCNN demonstrates effective gradient backpropagation and filter state training, thereby advancing Quantum Machine Learning for future applications.

2 Materials and Methods

In our work, we first apply preprocessing techniques such as resizing, rescaling, data augmentation and normalization. After completing the preprocessing, the modified images are fed as input to the encoding models, specifically FRQI and NEQR, to transform the classically represented cyclone images into quantum state images. Finally, the encoded images are trained using QCNN.

2.1 Flexible Representation of Quantum Image Representation (FRQI)

The FRQI works by encoding an image into a quantum state that captures both pixel intensity and spatial location. The pixel intensity is encoded in the amplitude of the quantum state, while the spatial location is encoded using phase parameters. The entire image is stored as a superposition of qubit states, which allows for parallel processing, as illustrated in Fig. 1. Quantum gates are subsequently applied to manipulate these states for various image operations, such as rotation, filtering, and transformations, taking advantage of the speed and efficiency of quantum computation. The representation of the FRQI state is specified in Eq. 1:

$$|I(\theta)\rangle = \frac{1}{2^n}\sum_{i=0}^{2^{2n}-1} (\cos(\theta_i)|0\rangle + \sin(\theta_i)|1\rangle) \otimes |i\rangle , \quad (1)$$

where,
|I⟩: quantum state of the image.
2n: total number of pixels in the image
|i⟩: basis state encoding the spatial position of the i-th pixel
θi: angle parameter encoding the grayscale or intensity value of the i-th pixel

2.2 Novel Enhanced Quantum Representation (NEQR)

NEQR is a method for encoding digital images into quantum states, emphasizing the efficient representation of pixel values and spatial information. Unlike FRQI, which encodes pixel intensities using angles (amplitudes), NEQR directly encodes grayscale or color pixel values as binary strings in qubit registers, as shown in Fig. 2. This approach allows for the exact representation

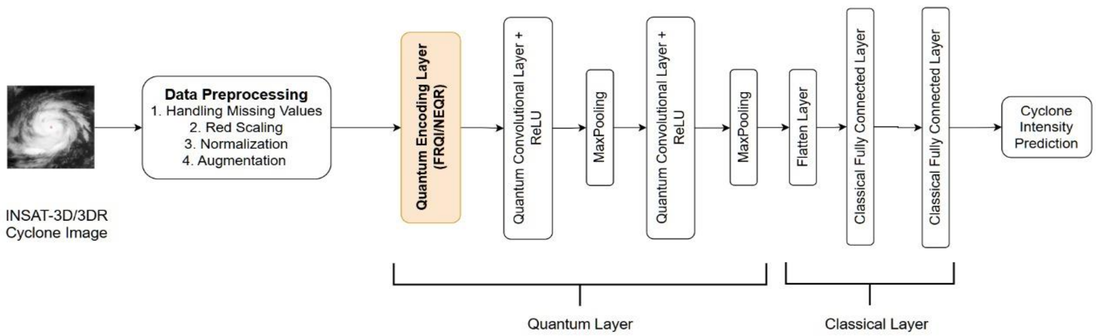

Fig. 3. QCNN Architecture for Tropical Cyclone Intensity + Prediction

of pixel values, making NEQR suitable for image processing tasks that require precise operations. For a digital image, NEQR encodes each pixel into a quantum state, as represented in Eq. 2.

$$|I\rangle = \frac{1}{2^n} \sum_{i=0}^{2^{2n}-1} |P_i\rangle \otimes |i\rangle \,, \quad (2)$$

where,

$|I\rangle$: quantum state of the image.

2^{2n}: total pixels in the image

$|P_i\rangle$: encoding the intensity value (grayscale or color) of the i^{th} pixel in binary form.

$|i\rangle$: encoding the spatial location of the i^{th} pixel.

2.3 Quantum Convolutional Neural Network Architecture

We utilize Quantum Convolutional Neural Network (Quantum CNN) architecture that integrates quantum circuit elements to replicate and enhance the functionalities of traditional CNNs. As illustrated in Figure 2, the Quantum CNN begins by encoding 16×16 grayscale images into quantum states using the FRQI encoder. This encoding process applies Hadamard gates to initialize the image qubits, followed by multi-controlled RY rotations that encode pixel intensities into the quantum state vector. This process is analogous to the convolutional layers in classical CNNs, which extract feature maps. In our Quantum Layer, translationally invariant unitary operations are systematically applied, mirroring the role of convolutional filters in capturing spatial hierarchies. To introduce nonlinearity, a pooling mechanism is implemented, where a subset of qubits is measured, and the outcomes dictate subsequent unitary transformations on neighboring qubits.

This effectively reduces the system's degrees of freedom, similar to the pooling layers in classical networks. This iterative process of convolution and pooling continues until the quantum state is sufficiently condensed. Subsequently, a fully connected layer, represented by a learned unitary operation, processes the remaining qubits to generate the final output.

2.4 Architecture

In Fig. 3, the QCNN Architecture for Tropical Cyclone Intensity Prediction is illustrated, showcasing the integration of quantum and classical layers for efficient feature extraction and prediction:

1. Input: INSAT-3D/3DR Cyclone Image:

The input to the model is a cyclone image obtained from the INSAT-3D/3DR satellite. These images contain essential information on cloud structure, temperature, and other meteorological features critical for predicting cyclone intensity.

2. Data Preprocessing:

Before the image is fed into the quantum encoding layer, it undergoes several preprocessing steps:

– Handling Missing Values: If any pixel data is missing or corrupted, interpolation or other

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Table 1. Performance Measures

Metric Name	Metric Formula
MSE	MSE = $\frac{1}{n}\sum_{m=1}^{n} e_m{}^2$
MAE	MAE = $\frac{1}{n}\sum_{m=1}^{n} \lvert e_m \rvert$
RMSE	RMSE= $\sqrt{\frac{1}{n}\sum_{m=1}^{n} e_m{}^2}$
R^2	$R^2 = 1 - \frac{SS_{residual}}{SS_{total}}$

Table 2. Performance Analysis of FRQI and NEQR with QCNN

	MSE	MAE	RMSE	R^2
FRQI-QCNN	0.0384	0.1535	0.1437	0.1961
NEQR-QCNN	0.0002	0.0061	0.0134	0.9959

techniques are employed to restore the data.

- Red Scaling: Red scaling is a preprocessing step in which the red channel of an image is adjusted and scaled to enhance feature extraction. The red channel often highlights cloud patterns, temperature variations, and cyclone structures more effectively.
- Normalization: Pixel values are normalized (e.g., between 0 and 1) to ensure uniformity and improve convergence during training.
- Augmentation: Data augmentation techniques (e.g., rotation, flipping,) are applied to improve model robustness and generalization.

3. Quantum Encoding Layer (FRQI/NEQR) :

   - The preprocessed image is then encoded into a quantum state using the Flexible Representation of Quantum Images (FRQI) or the Novel Enhanced Quantum Representation (NEQR).
   - FRQI encodes grayscale images by associating intensity values with quantum phase angles.
   - NEQR encodes pixel intensity directly into qubit states, enabling a more accurate representation.
   - This encoding transforms classical image data into quantum information, facilitating quantum processing.

4. Quantum Convolutional Layer + ReLU:

   - Once the image is encoded into a quantum state, it passes through a quantum convolutional layer (QConv layer).
   - Quantum convolution applies quantum gates (analogous to filters in classical CNNs) to extract spatial features.
   - The activation function utilized in this context is the Rectified Linear Unit (ReLU), which introduces non-linearity and facilitates the learning of complex patterns.

5. Quantum MaxPooling:

   - A quantum max-pooling operation is conducted to reduce dimensionality while preserving essential features.
   - This helps manage the number of qubits needed, thereby reducing computational complexity.

6. Second Quantum Convolutional Layer + ReLU:

   - A second quantum convolutional layer is applied, similar to the first, to extract higher-level features.
   - ReLU activation function is utilized once more to improve non-linearity in feature extraction.

7. Quantum MaxPooling:

   - Another quantum max-pooling step further reduces dimensionality, making the data more manageable for the subsequent classical processing.

8. Flatten Layer:

   - The quantum-processed image data is flattened into a 1D vector to prepare it for classical fully connected layers.

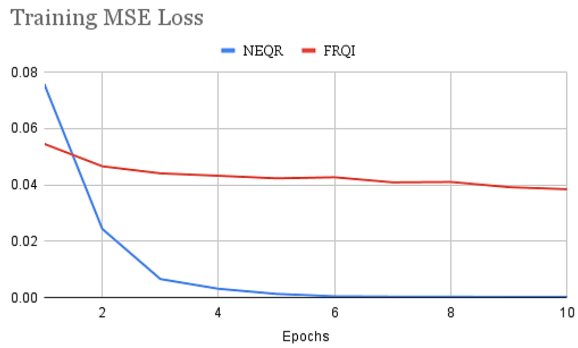

Fig 4. Comparative analysis of training loss for QCNN

9. Classical Fully Connected Layers:

   – The flattened quantum-processed features are passed to classical dense (fully connected) layers.
   – First Fully Connected Layer: Extracts key patterns from the quantum features.
   – Second Fully Connected Layer: Further refines the feature representation for the final output.

10. Cyclone Intensity Prediction:

   – The final layer outputs the predicted cyclone intensity based on the extracted features.

3 Results and Discussion

3.1 Dataset Description

We collected cyclones' data from Kaggle[1] [13] which contains INFRARED(IR) and RAW Cyclone Imagery from Indian Ocean 2012 to 2021 along with Cyclone Image intensity in KNOTS. We have considered the IR images for cyclone intensity prediction.

3.2 Performance Measure

We utilized the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) and R2 values as metrics to evaluate the model's performance for measuring the efficiency of the designed model as shown in Table 1 and Table 2.

It has been observed from Fig. 4 that the loss value for NEQR with QCNN converges way faster than FRQI with QCNN. At the end of 10 epochs NEQR has achieved significantly less loss than FRQI.

4 Conclusion

Quantum machine learning has garnered significant interest due to the rapid advancements in quantum technology in recent years. Accurate estimation of tropical cyclone (TC) intensity is essential for disaster prevention. While convolutional neural networks (CNNs) have improved this task, they struggle to capture global spatial relationships in images. Quantum Image Processing (QIP) leverages quantum parallelism and entanglement to encode and process images more effectively, utilizing methods such as FRQI and NEQR.

These techniques store pixel values and spatial coordinates in quantum states, allowing for an inherent representation of global patterns. Quantum systems can process data non-locally, making them well-suited for identifying structural patterns, such as cyclone spirals. QIP efficiently encodes high-dimensional information, requiring fewer resources than classical CNNs. NEQR improves image representation by encoding pixel intensity values as binary states, resulting in improved resolution and faster computation, which enables the QCNN to extract richer spatial features.

In our paper, we present a generalized implementation scheme for two popular encoding methods, FRQI and NEQR, to predict cyclone intensity. Experimental results demonstrate that NEQR with QCNN outperformed FRQI with QCNN.

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