Quantum Convolutional Neural Networks for Jet Images Classification

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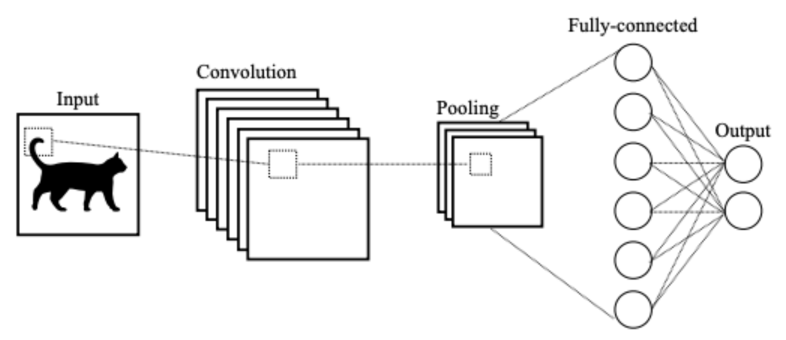
1 Introduction and motivation

- Quantum machine learning (QML) is expected to surpass classical machine learning in a wide range of instances.
- For example, when dealing with highly energetic jet images, classical convolutional neural networks (CNNs) fall short in classification accuracy.
- In this study, we use a quantum convolutional neural network (QCNN) and compare its classification accuracy with CNN using a classical simulator.

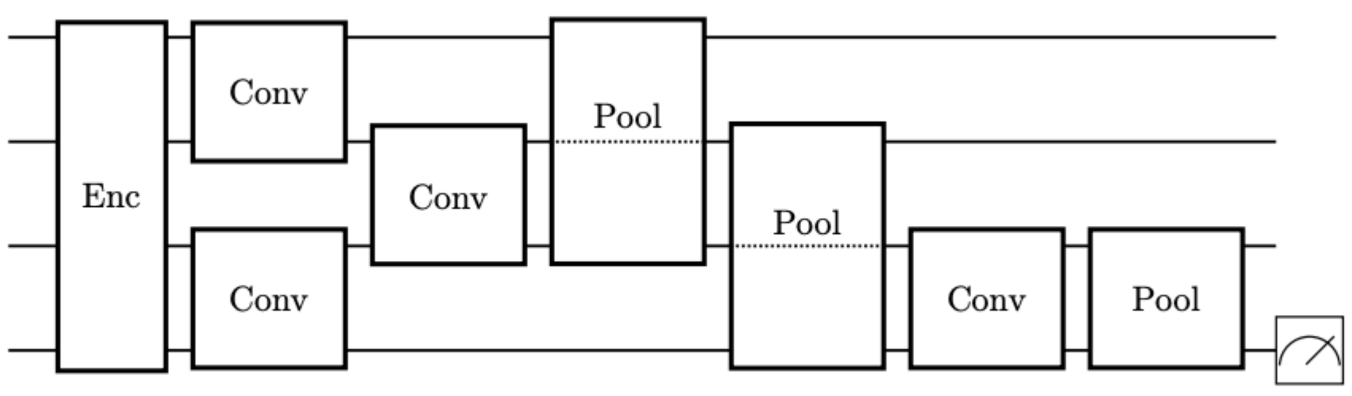
2 Methods

The main concept is to apply the convolutional and pooling tasks of CNNs for QCNNs.

- CNN:

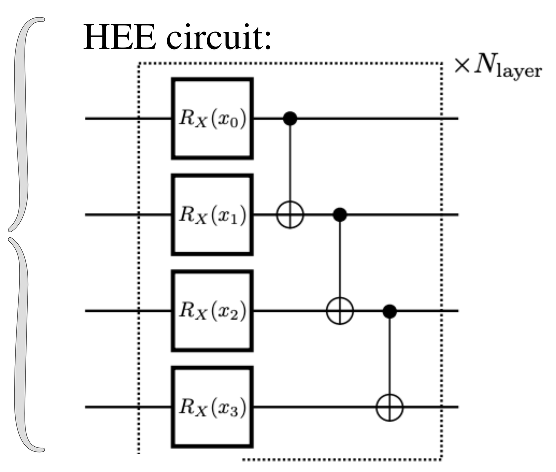


- QCNN:



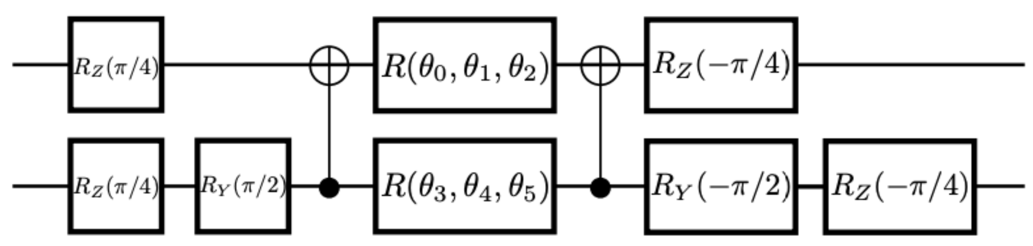
Encodings

- Tensor Product Embedding (TPE).
- Hardware Efficient Embedding (HEE).
- Classicaly Hard Embediing (CHE).

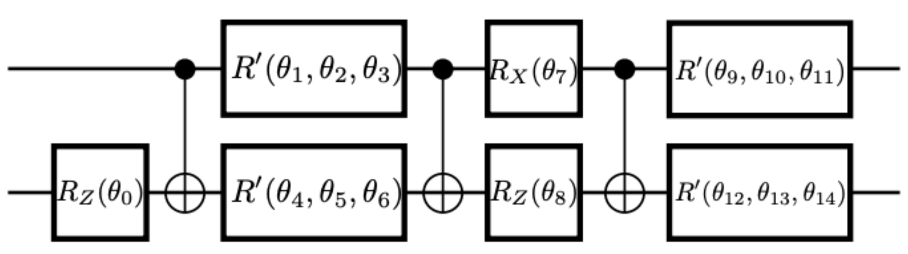


Conv. and Pool.

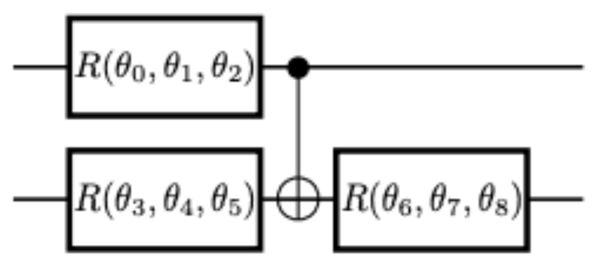
- SO(4):



- SU(4):



- Pool:



Loss functions

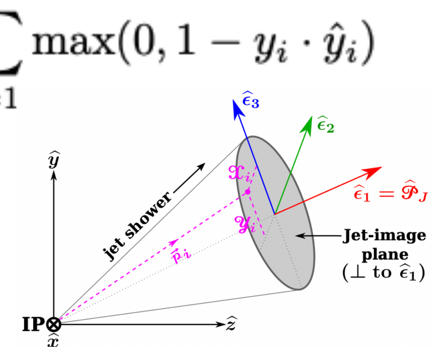
- For N inputs and y_i true-label, loss in $\hat{y}_i$ predictions are expressed as, e.g.:

$$\mathcal{L}_{\text{Cross-Entropy}} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right) ,$$

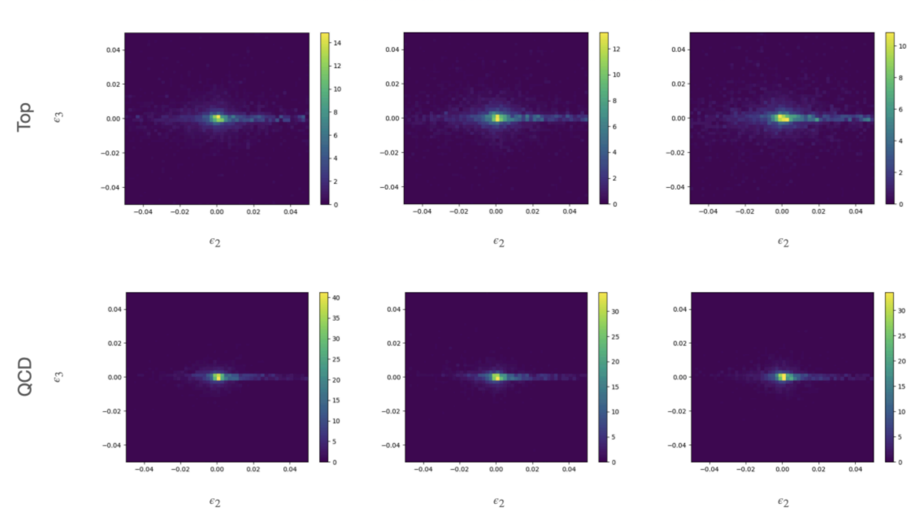
$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 , \mathcal{L}_{\text{Hinge}} = \frac{1}{N}\sum_{i=1}^{N}\max(0, 1-y_i\cdot\hat{y}_i)$$

Dataset

- Jet image: base of a jet cone plotted in a histogram filled with a fraction of the energies of the detected final state particles decayed from an original particle e.g. the top-quark or QCD.



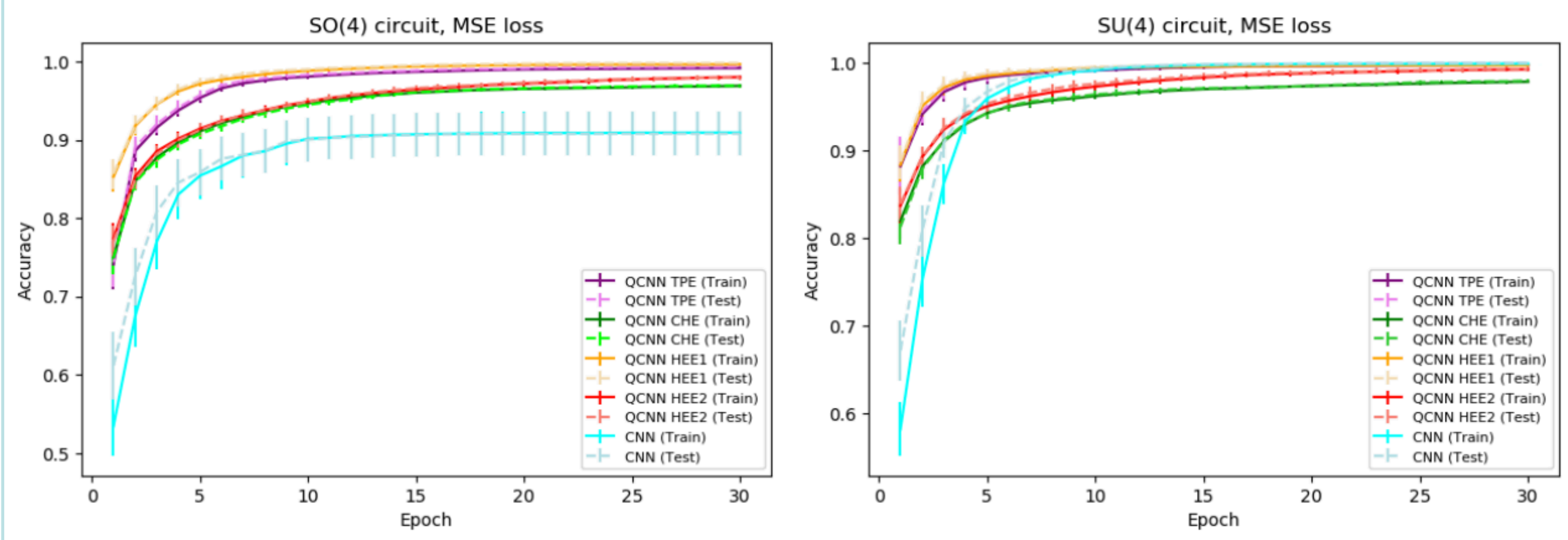
- 2k jet images classified
  - 1k top
  - 1k gcd



3 Results

- Batch-size $= 32$, averaged-runs $= 50$
- $\text{SO}(4)_{params-size} = 30 \rightarrow \text{CNN}_{params-size} = 33$
- $\text{SU}(4)_{params-size} = 48 \rightarrow \text{CNN}_{params-size} = 51$

Encoding dependence

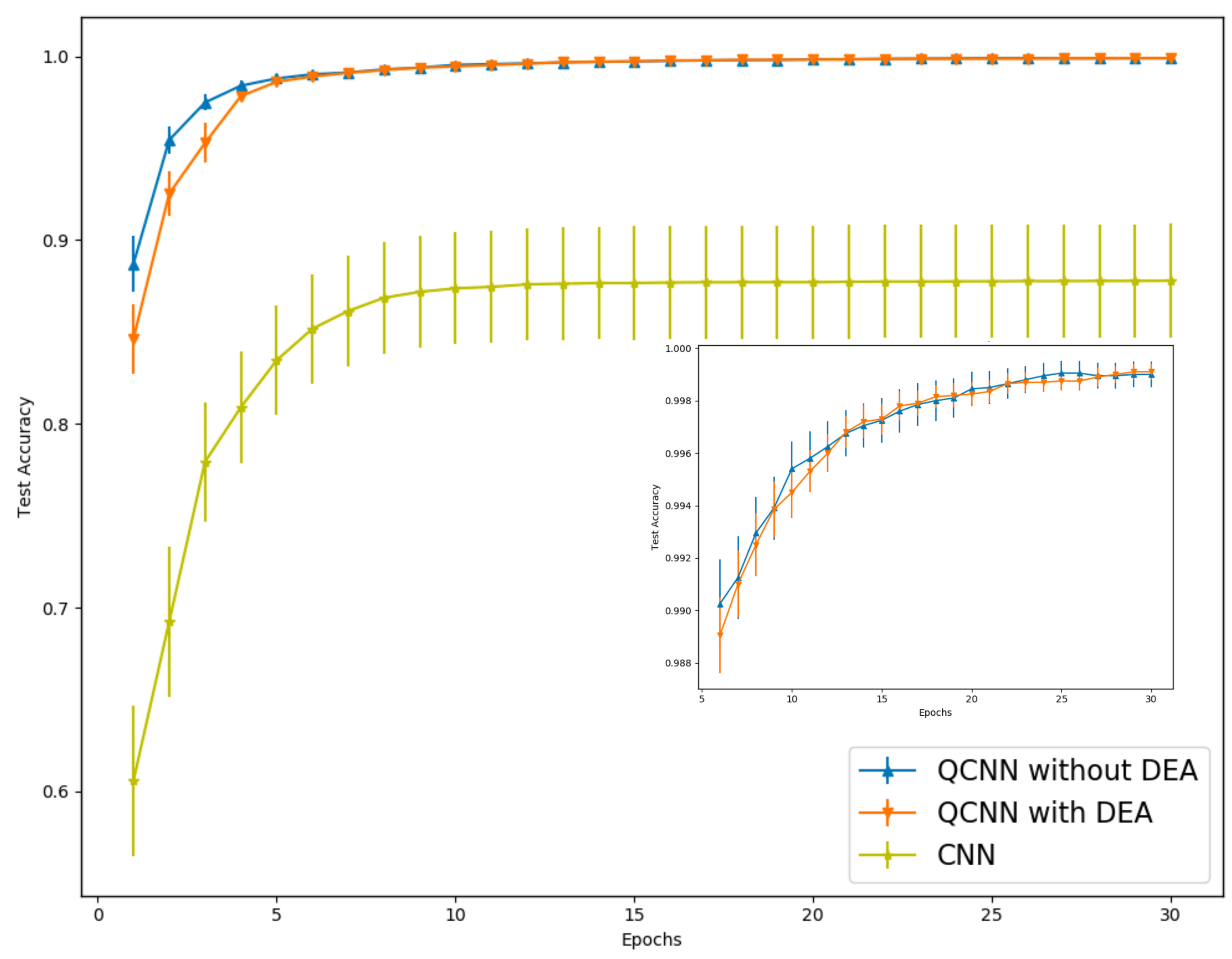


Circuit	Loss function	Encoding	QCNN Acc (%)	CNN Acc (%)
SU(4)	Hinge	TPE	99.36 ± 0.13	99.88 ± 0.05
		HEE1	**99.34 ± 0.10**	
		HEE2	98.30 ± 0.18	
		CHE	95.58 ± 0.34	
	MSE	TPE	99.93 ± 0.03	99.95 ± 0.02
		HEE1	**99.90 ± 0.05**	
		HEE2	99.28 ± 0.11	
		CHE	97.97 ± 0.12	
	Cross-entropy	TPE	99.58 ± 0.08	99.92 ± 0.03
		HEE1	**99.62 ± 0.05**	
		HEE2	98.62 ± 0.16	
		CHE	96.70 ± 0.18	

Dimensional expressivity analysis[1] (work in progress)

Dimensional expressivity analysis (DEA) performed to get optimal maximally expressive circuit with the least number of trainable parameters.

Circuit structure	params.	Acc (%)
SU(4) without DEA	48	**99.90 ± 0.05**
SU(4) with DEA	31	99.91 ± 0.03
CNN	33	87.79 ± 3.09



4 Conclusions

- All QCNN setups conveyed faster convergence compared to CNNs.
- Higher params-size indicated better accuracy of CNN compared to QCNN.
- QCNN showed better accuracy at the level of low params-size (e.g. SO(4) and DEA circuit).
- Further DEA studies are undergoing trials to reduce the run-time before performing real hardware runs.

1. L. Funcke, T. Hartung, K. Jansen, S. Kühn, M. Schneider, and P. Stornati, Dimensional expressivity analysis, best-approximation errors, and automated design of parametric quantum circuits (2021), arXiv:2111.11489 [quant-ph], DOI: https://doi.org/10.22323/1.396.0575.