Midterm Evaluation:

EQUIVARIANT QUANTUM NEURAL NETWORKS FOR HIGH ENERGY PHYSICS ANALYSIS AT THE LHC

Mentors: Konstantin Matchev, Katia Matcheva, KC Kong.

Contributor: Lazaro R. Diaz Lievano

Google Summer of Code @ ML4SCI Machine Learning for Science

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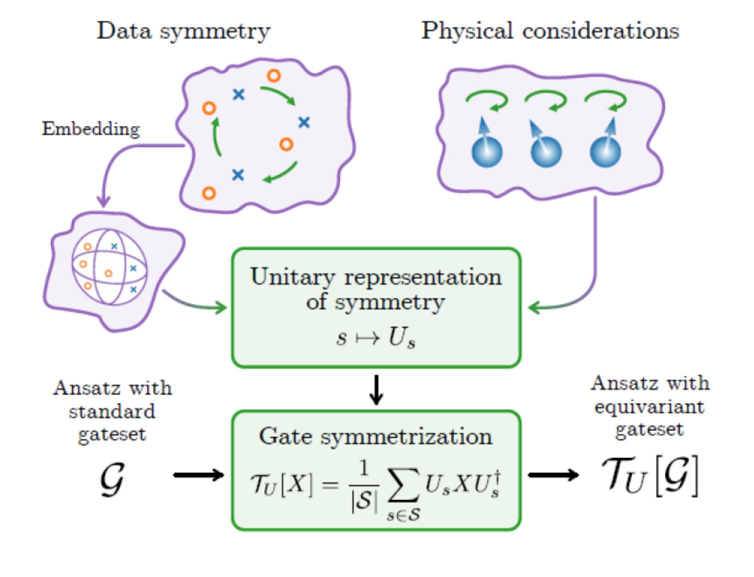
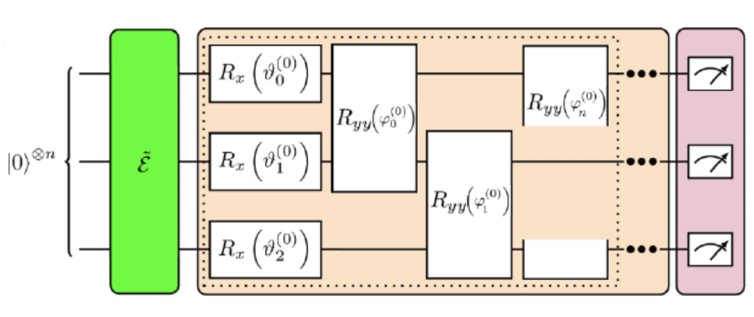
Introduction





An EQNN is a quantum network that respects the symmetry of the data, i.e., the outcome y(θ, x) is invariant under the symmetry operation S.

$$y(\theta, U_s[x]) = \langle \psi(\theta, U_s[x]) | O_{\text{Inv}} | \psi(\theta, U_s[x]) \rangle = y(\theta, x)$$

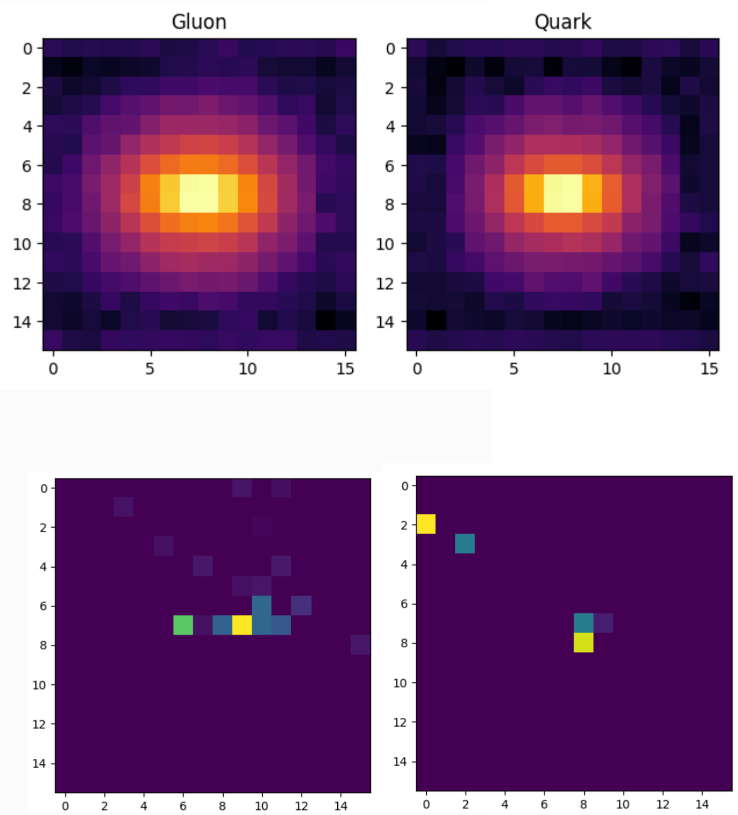
An EQNN consists of three elements:

- Equivariant Embedding method
- Equivariant Ansatz
- Invariant Measurement

Objective:

In this project, we want to explore the use of EQNN for High-Energy Physics problems.

For that, we consider symmetries widely found in image analysis like *Rotations, Reflections* and *Traslations.*



Previous Works

In the literature, we can find some papers about EQNN for image classification as West, Maxwell T., et al. [1] and Chang, Su Yeon, et al. [2].

We based over their research to follow on our project for HEP. However, the code is not public.

Reflection Equivariant Quantum Neural Networks for Enhanced Image Classification

Maxwell West,[1,*] Martin Sevior,[1] and Muhammad Usman[1,2,†]
[1]School of Physics, The University of Melbourne, Parkville, 3010, VIC, Australia
[2]Data61, CSIRO, Clayton, 3168, VIC, Australia

Generic quantum machine learning (QML) architectures often suffer from severe trainability issues and poor generalisation performance. Recent work has suggested that geometric QML (GQML) may combat these issues through the construction of targeted QML models which explicitly respect the symmetries of their data. Here we turn the techniques of GQML to image classification, building new QML models which are equivariant with respect to reflections of the images. Our results are the first to demonstrate that this class of QML models is capable of consistently outperforming widely used generic ansatze, highlighting the potential for the future development of superior QML networks by directly exploiting the symmetries of datasets.

Approximately Equivariant Quantum Neural Network for $p4m$ Group Symmetries in Images

Su Yeon Chang*†, Michele Grossi*, Bertrand Le Saux‡ and Sofia Vallecorsa*
*IT Department, European Organization for Nuclear Research (CERN), CH-1211 Geneva, Switzerland
† Laboratory of Theoretical Physics of Nanosystems (LTPN), Institute of Physics, École Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland
‡Φ-lab European Space Agency, IT-00044, Italy
Email: su.yeon.chang@cern.ch

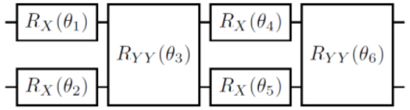
West, Maxwell T., et al. Reflection Equivariant Quantum Neural Networks for Enhanced Image Classification. *Machine Learning: Science and Technology*, vol. 4, n.º 3, septiembre de 2023, p. 035027.

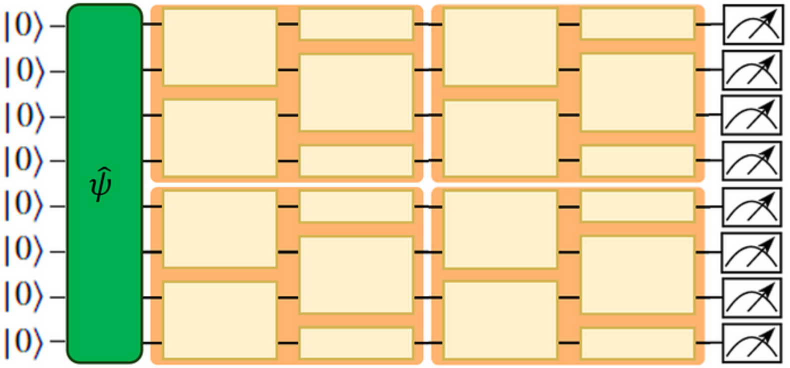
Chang, Su Yeon, et al. «Approximately Equivariant Quantum Neural Network for $p4m$ Group Symmetries in Images». 2023 IEEE International Conference on Quantum Computing and Engineering (QCE), 2023, pp. 229-35.

Implementation

EQCNN

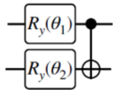
U2_equiv



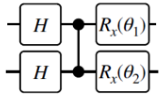


QCNN

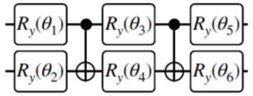
U_TTN



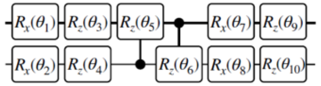
U_9

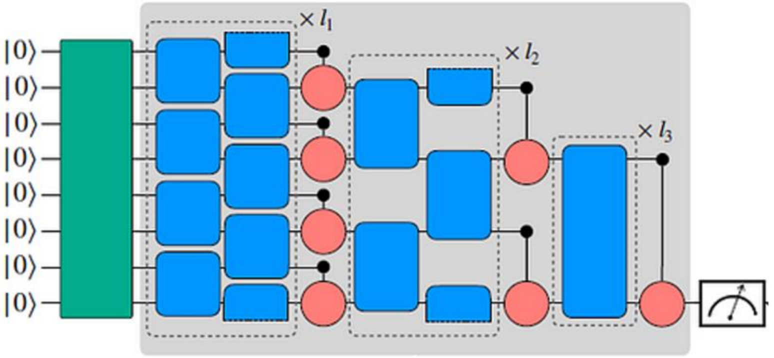


U_15



U_5

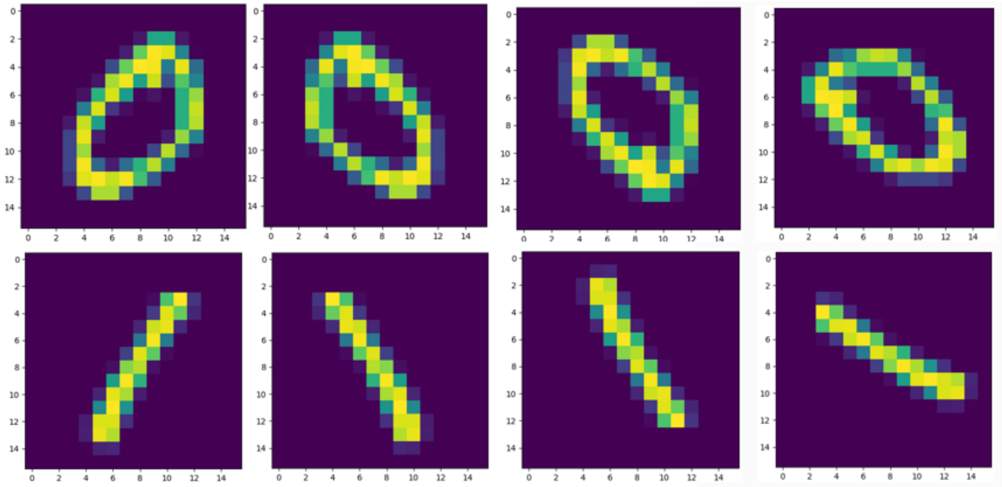




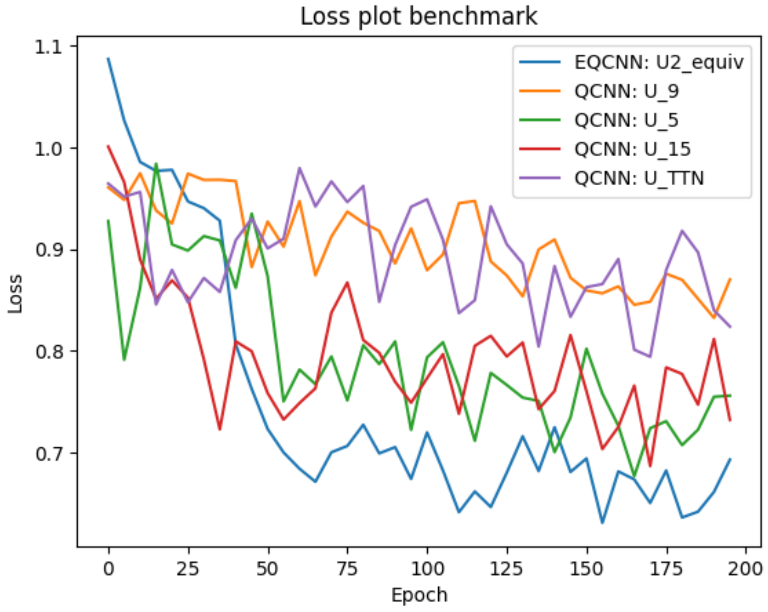
West, Maxwell T., et al. Reflection Equivariant Quantum Neural Networks for Enhanced Image Classification. *Machine Learning: Science and Technology*, vol. 4, n.º 3, septiembre de 2023, p. 035027.

Chang, Su Yeon, et al. «Approximately Equivariant Quantum Neural Network for $p4m$ Group Symmetries in Images». 2023 IEEE International Conference on Quantum Computing and Engineering (QCE), 2023, pp. 229-35.

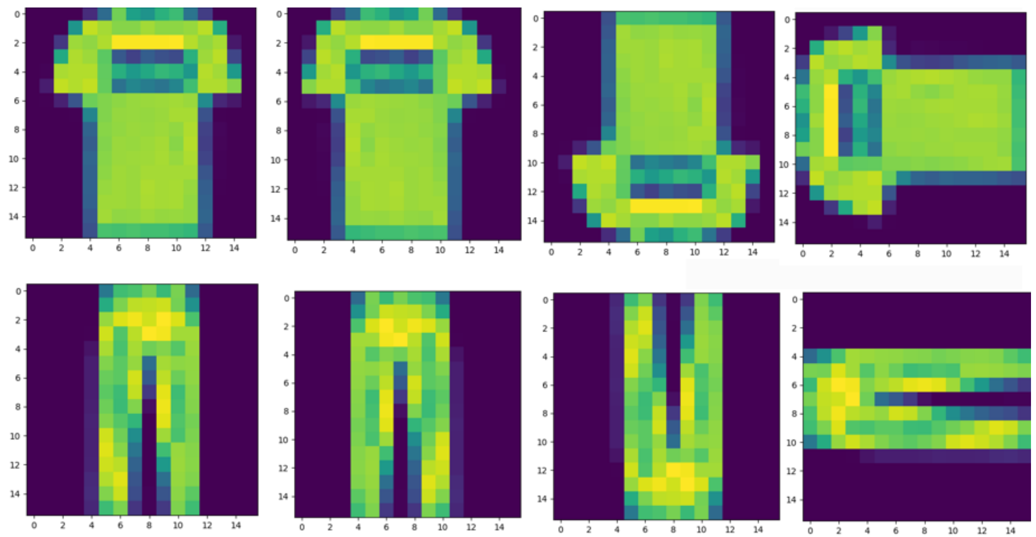
Examples: MNIST dataset


Original | Reflected over X | Reflected over Y | Rotated by 90°

12k training. 2k test. 200 epochs (<40 min). MSE cost. Nesterov optimizer. l_r = 0.01

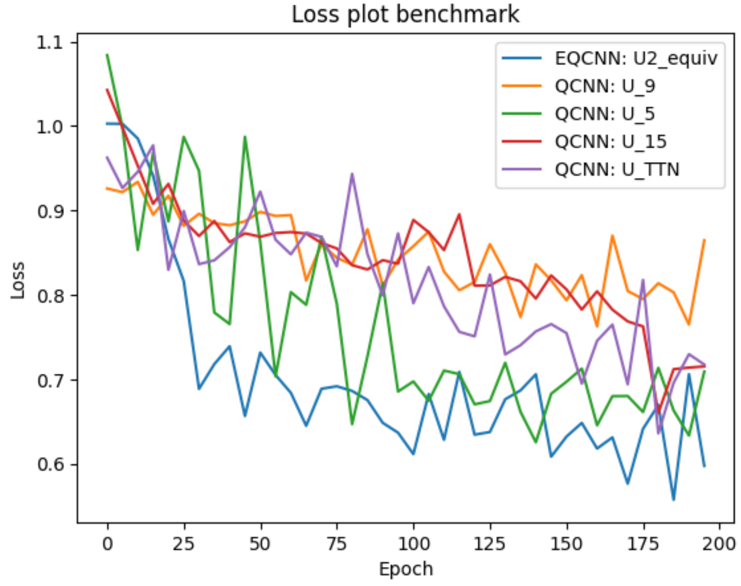


Model	Accuracy	params
EQCNN: U2_equiv	0.9664	12
QCNN: U_9	0.9404	12
QCNN: U_5	0.9361	36
QCNN: U_15	0.7569	20
QCNN: U_TTN	0.5919	12



Original Reflected over X Reflected over Y Rotated by 90°

12k training. 2k test. 200 epochs (<40 min). MSE cost. Nesterov optimizer. l_r = 0.01

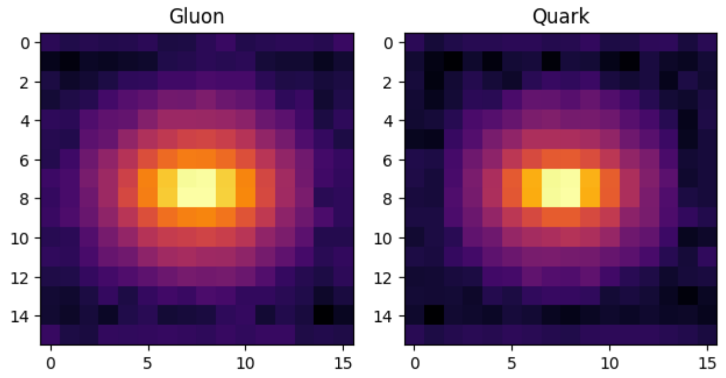


Modelo	Accuracy	params
U2_equiv img16x16x1	0.877	12
U_15 img16x16x1	0.8555	20
U_5 img16x16x1	0.8505	36
U_TTN img16x16x1	0.8085	12
U_9 img16x16x1	0.7335	12

Next Steps

- Apply these models on High Energy Physics datasets like the the Quark-Gluon dataset or the Electron-Photon dataset.

- Explore different architectures of EQCNN.



[Project blog post]

[Github Repository]

References

[1] West, Maxwell T., et al. *Reflection Equivariant Quantum Neural Networks for Enhanced Image Classification.* Machine Learning: Science and Technology, vol. 4, n.o 3, septiembre de 2023, p. 035027.
[2] Chang, Su Yeon, et al. *Approximately Equivariant Quantum Neural Network for $p4m$ Group Symmetries in Images.* 2023 IEEE International Conference on Quantum Computing and Engineering (QCE), 2023, pp. 229-35.