Photonic machine learning for image classification

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Data re-uploading is a well established method in the realm of Quantum Machine Learning (QML). In our work we realised a photonic version of such a single qubit classifier on a variety of datasets of different complexity and dimensionality in an optical integrated circuit. This constitutes an important first step to transfer the possible energy-efficiency gains from classical photonic chips to QML.

Data re-uploading [1] is a well studied quantum machine learning technique. It offers the capabilities of a universal approximator, under certain requirements, with just a single qubit and rotation operations [2, 3]. In the same fashion as in classical Neural Networks the input data is reintroduced to the learning system multiple times. While this can be easily achieved in a classical network by simply copying the input data, for a quantum variant, due to the non-cloning theorem, one must introduce the data multiple times. Herewith the quantum algorithm is structured in distinct layers. Each layer consist of an encoding unitary U_{enc}, where the input data is encoded, and a trainable unitary U_{ϑ}, with free tune-able parameters. Hence the overall operation of the circuit reads as follows:

$$|\Psi_{out}\rangle = \prod_{l=1}^{L} [U_{enc}(\vec{x}) U(\vec{\theta_l})] \, |\Psi_{in}\rangle \tag{1}$$

As shown is several publications such a structure act as a universal approximator[2–4]. In this scheme one makes use of the non-linear operation, which ones obtains by direct encoding of the input data in a rotation gate.

The expressivity is simply dependent on the amount of sequential encoding and training unitaries. While this approach is less suited for superconducting qubits, due to a very limited coherence time, this is extremely suitable for photonic qubits. Furthermore, since we only require a single qubit for the data re-uploading QML algorithm, we use a weak coherent laser-light in a two mode system to perform the machine learning tasks. In this picture we can implement any unitary operation, up to a global phase in the computational basis, by a single Mach-Zehnder interferometer (Figure 1), consisting of two 50/50-beamsplitters and an internal and external phase-shifter [5]. Note that we can implement multiple layers through a single Mach-Zehnder interferomenter, since we can express the product of unitaries as a single unitary.

In this work, we realised such a data re-uploading scheme in an integrated optical chip, enabling the possibility of transferring the energy efficiency gains of a classical optical chip to a quantum machine learning algorithm. Furthermore, we used Linear Discreminant Analysis to find the linear seperation on the single dimensional bonded outputspace as a classification.

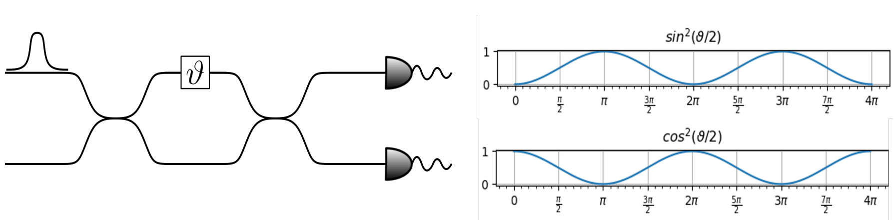

FIG. 1: **Integrated Mach-Zehnder Interferometer.** Mach-Zehnder interferometer without an external phase shifter. Hereby the output distribution depends in a non-linear way on the phase ϑ, constituting the inputs.

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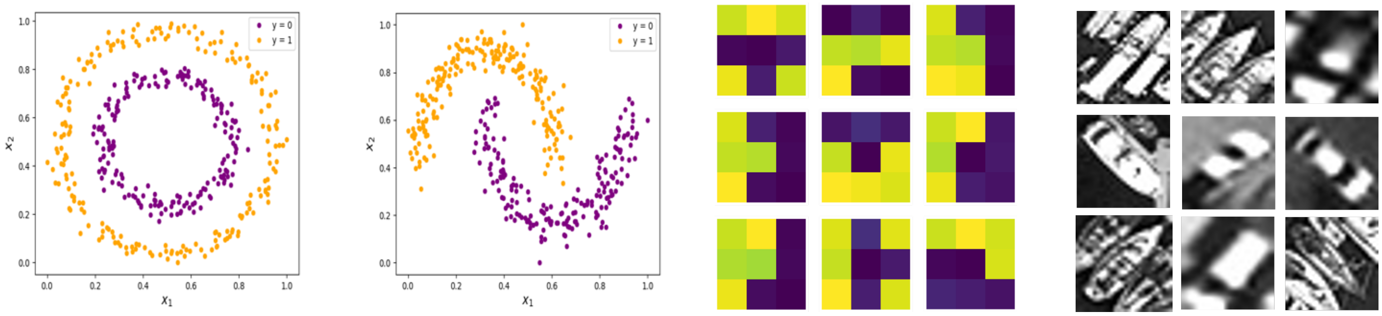


(a) Circles (b) Moons (c) Tetrominos (d) Overhead MNIST

FIG. 2: **Datasets of different complexity and dimensionality used in the experimental realisation.** (a) Circles and (b) Moons are generated by the scikit-learn python library [6]. (c) Two possible Tetrominos, i.e. "L" and "T", and there negative mask in a 3 by 3 grid. (d) Two classes from the Overhead MNIST dataset [7], i.e. "Car" and "Ship". The last data set was reduced using Principal Component Analysis to 20 features.

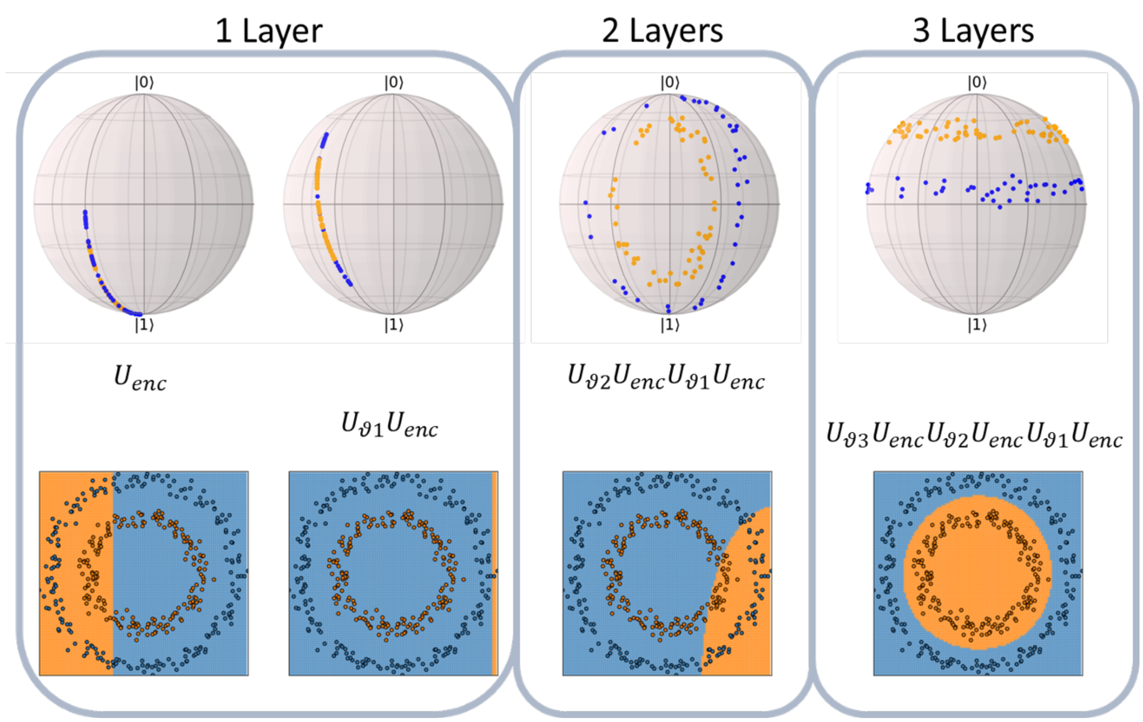
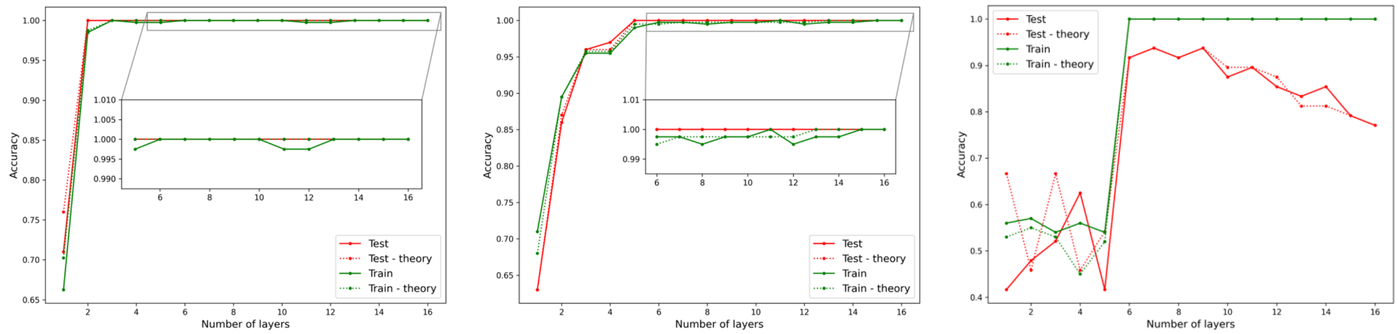


FIG. 3: **Visualisation of a three layered single qubit classifier on the circles dataset.** The top row shows the action after x layer(s) on all of the output states on the Bloch sphere. The middle row denotes the operations applied to our fixed input state. The last row, shows the encoded data set - orange and blue points in the arrangement of two concentric circles with different radii - and the predicted label by the classifier via the background colour.

In addition, the suggested approach, with all its resource-efficiency improvements, seem to be robust enough, that the protocol leads to the same results for both noise-less simulation and a noise heavy experimental realisation.

Hereby, a wide variety of different datasets were investigated (Figure 2). The first two examined datasets are the two dimensional Circles (Figure 2a) and Moons (Figure 2b) dataset. These two differ mainly by the required non-linearity to solve them. A visualisation of this data re-uploading ansatz on the circles dataset is shown in Figure 3.

Since both of the two datasets can be solved with only a small number of layers, we increased the complexity of the task, by evaluating higher dimensional data. In order to incorporate more than two features, which are implementable on a single Mach-Zehnder-Interferometer, we utilised a sequential approach, i.e. splitting the data up in pairs and



(a) Circles (b) Moons (c) Tetrominos

FIG. 4: **Achieved accuracy vs. model dimension.** The green curves plot the performance on the training data, while the red curves visualise the performance on unseen test data. The dotted and solid lines represent the theoretical/simulated and the performance on the optical integrated circuit respectively.

implement one pair after another in the single qubit rotations, always followed by a trainable gate operation. The complete set of all unitaries for encoding the complete dataset and the following trainable gates form a single layer of the data re-uploading quantum learning system [8].

In this way, larger 3x3 image classification of Tetrominos (Figure 2c), as well as the binary classification of satellite images (Figure 2d) after a dimensionality reduction to 20 features, were performed.

In the first iteration the training procedure was performed, with the python libraries TensorFlow [9] and Strawberry Fields [10, 11], to ensure good convergence, before running the prediction on real hardware. The resulting performance for the first three datasets are depicted in Figure 4. For the last examined dataset, i.e. parts of the Overhead MNIST dataset [7], we only optimised the scenario with four layers, which yielded a accuracy of 86.15% (train) and 85.14% (test). In contrast a linear classifier on this task is only able to achieve 82.32% and 81.08% respectively.

In the following, in order to demonstrate the feasibility of this algorithm implemented solely in quantum hardware, we first also performed some experiments without compressing the unitaries. Furthermore, since the biggest hurdle for data re-uploading is the required training of the circuit, we successfully trained the model directly on chip, through parameter shift [12, 13].

[1] Pérez-Salinas, A., Cervera-Lierta, A., Gil-Fuster, E. & Latorre, J. I. Data re-uploading for a universal quantum classifier. Quantum 4, 226 (2020).

[2] Schuld, M., Sweke, R. & Meyer, J. J. Effect of data encoding on the expressive power of variational quantum-machine-learning models. Phys. Rev. A 103, 032430 (2021).

[3] Goto, T., Tran, Q. H. & Nakajima, K. Universal Approximation Property of Quantum Machine Learning Models in Quantum-Enhanced Feature Spaces. Phys. Rev. Lett. 127, 090506 (2021).

[4] Yu, Z., Yao, H., Li, M. & Wang, X. Power and limitations of single-qubit native quantum neural networks. Preprint at arXiv.2205.07848 (2022).

[5] Clements, W. R., Humphreys, P. C., Metcalf, B. J., Kolthammer, W. S. & Walmsley, I. A. Optimal design for universal multiport interferometers. Optica, OPTICA 3, 1460–1465 (2016).

[6] Pedregosa, F. et al. Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 12, 2825–2830 (2011).

[7] Noever, D. & Noever, S. E. M. Overhead MNIST: A Benchmark Satellite Dataset. Preprint at arXiv.2102.04266 (2021).

[8] Periyasamy, M. et al. Incremental Data-Uploading for Full-Quantum Classification. in 2022 IEEE International Conference on Quantum Computing and Engineering (QCE) 31–37 (2022).

[9] Developers, T. TensorFlow. (2023) doi:10.5281/zenodo.10126399.

[10] Killoran, N. et al. Strawberry Fields: A Software Platform for Photonic Quantum Computing. Quantum 3, 129 (2019).

[11] Bromley, T. R. et al. Applications of Near-Term Photonic Quantum Computers: Software and Algorithms. Quantum Sci. Technol. 5, 034010 (2020).

[12] Mitarai, K., Negoro, M., Kitagawa, M. & Fujii, K. Quantum Circuit Learning. Phys. Rev. A 98, 032309 (2018).

[13] Schuld, M., Bergholm, V., Gogolin, C., Izaac, J. & Killoran, N. Evaluating analytic gradients on quantum hardware. Phys. Rev. A 99, 032331 (2019).