Quantum Classifiers for Remote Sensing

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ABSTRACT

Hybrid classic-quantum systems utilized existing quantum hardware for machine learning (ML) by running pre- and post-processing on classic hardware to overcome the limitations of today's quantum computers. In this work, hybrid systems with several pre-processing techniques and two circuit architectures are evaluated by classifying remote sensing (RS) imagery. The potential of quantum machine learning (QML) for RS is investigated and particularly autoencoder methods are found to be suitable for pre-processing. The code is published in an open repository: https://github.com/tumbgd/qc4rs.

CCS CONCEPTS

• **Computer systems organization** → **Quantum computing**.

KEYWORDS

quantum computing, hybrid system, supervised classification, remote sensing, dimensionality reduction

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1 INTRODUCTION

Quantum supremacy, which is the ability to solve computational problems in a reasonable time that is out of reach for classic supercomputers, has been theoretically demonstrated for a highly abstract task [1]. Quantum computers exploit the superposition and entanglement of a qubit, which allows it to follow different paths of computation at the same time [9]. Additional, recent advantages in the development of prototypes for quantum computers have further driven the research in the rising field of quantum computing. Parameterized quantum circuits (PQCs) are a way to implement algorithms on quantum hardware and have been successfully used as ML models for the classification of classic data within hybrid systems [2]. Generally, a quantum circuit consists of unitary transformations U_i, which are also called quantum gates and act on the quantum state $|\psi\rangle$. A circuit $\hat{U}_\theta$ can be built from a set $\{U_i(\theta_i)\}$ of such parameterized unitary operators. Then, a PQC $\hat{U}_{x,\theta} = \hat{U}_\theta \hat{U}_x$ consists of an encoder circuit $\hat{U}_x$ and a variational circuit $\hat{U}_\theta$. The encoder circuit is parameterized by the input data x and encodes it into quantum state. The variational circuit is parameterized by a set of parameters θ, which can be optimized by minimizing a loss function and acts on the quantum state $|\psi\rangle$. In this work, the optimizer of choice is Adaptive Moment Estimation. Now, a PQC as ML model is defined by:

$$f_\theta(x) = \langle\psi|\hat{U}^\dagger_{x,\theta} M \hat{U}_{x,\theta}|\psi\rangle = \langle M\rangle_{x,\theta} \quad (1)$$

where M is a Hermitian operator, which is one of the Pauli matrices representing an observable, and $\langle M\rangle_{x,\theta}$ is the measured expectation value, which is the output of the model and mapped to the prediction $\hat{y}$ for the label y of the input data x. However, large-scale fault-tolerant quantum computers are still out of reach, and due to noise in quantum hardware, only short sequences of operations and a limited amount of qubits can be realized. A workaround is hybrid classic-quantum systems (Fig.: 1). The pre-processing, which is the feature extraction and dimensionality reduction, and the post-processing, which is the parameter updating, are done classic to reduce the requirements of quantum hardware. Already today, hybrid systems successfully use existing quantum hardware for scaled-down ML problems, and several successful attempts at the classification of computer vision datasets, like handwritten digits, were presented in the literature [2]. Particularly the pre-processing is important for the application of QML in RS since the images do not fit into the limited input domain of the PQCs. Even if more realizable qubits become available the input domain should be as small as possible, while obtaining a meaningful representation of the data, to counter noise in quantum hardware. Furthermore, data reduction is important to create meaningful features to support classification, reduce the computational effort and avoid problems like the curse of dimensionality and overfitting on the training data. Several classic pre-processing methods are thus implemented inside hybrid systems with two PQCs for classification in different configurations and two RS image datasets are used for evaluation.

2 METHODOLOGY

Nine preprocessing techniques, which generally reduce the input image to $K = 16$ elements, were evaluated within hybrid systems. Besides downscaling and the linear dimensionality reduction methods principal component analysis and factor analysis, several autoencoder models are implemented. Single- and multi-layer autoencoder, convolutional autoencoder, and autoencoder created from pretrained restricted Boltzmann machines are tested. Additionally, a very deep convolutional network with 16 layers (VGG16) [8] is used without the fully connected top layers to extract features before the dimensionality reduction techniques in an attempt to increase the classification accuracy of the PQCs. For the embedding of the reduced classic data into quantum state, basis and angle encoding was considered. The quantum systems are simulated on classic hardware and the circuit architectures were previously presented in the literature. The FPQC, which is based on [4], already gave

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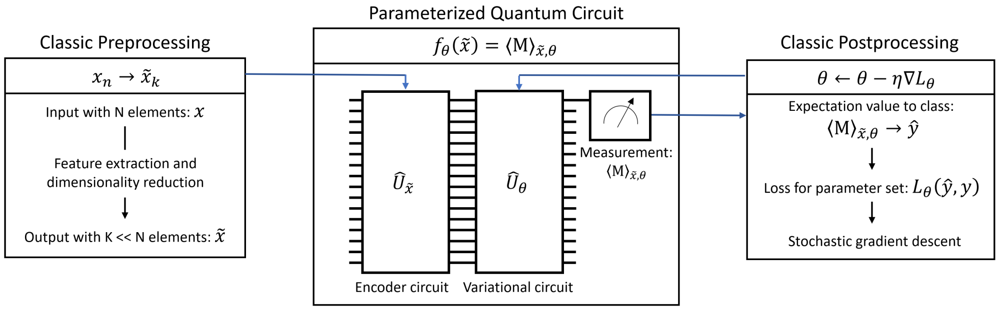

Figure 1: General scheme of the hybrid systems.

promising results for the classification of earth observation imagery [7]. Furthermore, the GPQC based on [5] was successfully used for the classification of handwritten digits [5]. Both architectures are used with an input space of $K = 16$ data qubits q_k while the FPQC has one additional readout qubit q_r.A single qubit is measured to obtain an expectation value for the label of input data (Eqn.: 1). Furthermore, the three Pauli observables and three loss functions, which are hinge loss, square hinge loss, and binary cross-entropy loss, were considered. Classification was also attempted classic with two dense layers instead of a PQC. Since the FPQC has 32 and the GPQC 31 trainable parameters, a classic approach with 37 trainable parameters presents a fair comparison. All experiments were carried out with two datasets: EuroSAT [6] and RESISC45 [3].

3 EXPERIMENTS AND RESULTS

Grid searches for both circuit architectures were conducted to find the most promising configuration of encoding method, observable, and loss function. While the impact of the chosen loss function was low, the choice of encoding method and quantum observable should be taken with care. Based on grid searches, two suitable configurations for each circuit were chosen for further experiments. Two binary classification tasks from both datasets were used to evaluate hybrid systems with the PQCs and nine pre-processing techniques each. The hybrid systems achieved high accuracies, especially the FPQC, which achieved $> 95\%$ in some instances for both datasets with autoencoder models for pre-processing. Overall, autoencoder models outperformed other reduction techniques. For both circuits, hybrid systems with prior feature extraction by a VGG16 in combination with a deep autoencoder resulted in the highest accuracy scores with the EuroSAT data, while hybrid systems with the convolutional autoencoder performed best with RESISC45. The classic dense layer approach achieved results similar to a PQC and was even outperformed by the FPQC in some instances. In a one-versus-rest (OvR) attempt on multiclass classification, it was found that the outputs of the individual OvR classifiers did not lead to meaningful comparable magnitudes. Nevertheless, a hybrid system containing the VGG16, a deep autoencoder, and the FPQC resulted in a mean accuracy of 57.11% over five runs and the best run in 59.50% for classification of the EuroSAT dataset. The individual OvR classifiers resulted in accuracies of about 90%, similar to the classic approach. However, the classic approach outperformed the hybrid systems with a mean overall accuracy of 69.61%, and the hybrid systems which contained the GPQC did, in general, not lead to meaningful results for multiclass classification. No sufficient results could be obtained for multiclass classification of the RESISC45 dataset with any of the hybrid systems.

4 CONCLUSION

Deep autoencoder and convolutional autoencoder were shown to be best suited for the pre-processing and resulted in meaningful small-scale representations for the RS imagery. Furthermore, the FPQC was found to achieve higher accuracy and loss scores than the GPQC for every classification task. However, this may change with quantum noise due to the lower circuit depth of the GPQC with ≥ 9 consecutive gates compared to the FPQC with a depth of ≥ 35. Overall, the hybrid systems achieved similar accuracies compared to the simple classic approach. It is worth noting, that the learning curves of the OvR quantum classifiers showed that training over three epochs is enough for both circuits since loss and accuracy did not significantly change after. Since the magnitudes of the OvR classifier outputs are not reasonably comparable, future work is to test probability calibration for the OvR classifiers. The findings imply that small-scale quantum systems have potential for RS and if large-scale and error-corrected hardware becomes available, and a computational speed-up compared to classic approaches can be realized, QML may become a new way to process RS imagery.

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