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Exploiting the Quantum Advantage for Satellite Image Processing: Quantum Resource Estimation

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ABSTRACT We first review the current state of the art of quantum computing for Earth observation (EO) and satellite images. There are the persisting challenges of profiting from quantum advantage, and finding the optimal sharing between high-performance computing (HPC) and quantum computing (QC), i.e. the HPC+QC paradigm, for computational EO problems. Secondly, we assess some parameterized quantum circuit models transpiled into a Clifford+T universal gate set, where the Clifford+T quantum gate set sheds light on the quantum resources required for deploying quantum models either on an HPC system or several QCs. If the Clifford+T quantum gate set cannot be simulated efficiently on an HPC system then we can apply a quantum computer and its computational power over conventional computers. Our resulting quantum resource estimation demonstrates that Quantum Machine Learning (QML) models having a sufficient number of T-gates provide the quantum advantage if and only if they generalize on unseen data points better than their classical counterparts deployed on the HPC system and they break the symmetry in their weights at each learning iteration like in conventional deep neural networks. As an initial innovation, we estimate the quantum resources required for some QML models. Secondly, we define the optimal sharing between an HPC+QC system for executing QML models for Hyperspectral Satellite Images (HSIs); HSIs are a unique dataset compared to multispectral images to be deployed on quantum computers due to the limited number of their input qubits, and the commonly used small number of labeled benchmark HSIs.

INDEX TERMS Earth observation, hyperspectral images, image classification, quantum machine learning, quantum computers, quantum resource estimation, remote sensing.

I. INTRODUCTION

A. WHY QUANTUM COMPUTING FOR EARTH OBSERVATION?

EARTH Observation (EO) methodologies tackle optimization and Artificial Intelligence (AI) problems involving big datasets obtained from instruments mounted on space-borne and airborne platforms. Some optimization and AI problems combined with big EO datasets are intractable computational problems for conventional High Performance Computing (HPC) systems. In addition, EO datasets themselves are complex heterogeneous image datasets, compared with conventional Red-Green-Blue (RGB) images, characterized by so-called 4V features comprising volume, variety, velocity, and veracity [1]; here, volume refers to big EO datasets (e.g. Terabytes of data per day collected, for instance, by the European Space Agency), variety refers to distinct spectral data such as multispectral, and hyperspectral pixel data, velocity refers to the speed of change on the Earth's surface, and veracity refers to imperfect datasets such as noisy images or remotely-sensed images partly covered by clouds [2]. In general, EO problems also include calibration and integer optimization problems in Synthetic Aperture Radar (SAR) applications [3], [4], a Bayesian paradigm (e.g. Gaussian processes) for retrieving physical parameters from remotely-sensed datasets [5], [6], uncertainty estimates for EO predictions [7], solving Partial Differential Equations (PDEs) for climate modeling and digital twin Earth paradigms [8], and identifying objects on the Earth's surface [9]. Furthermore, integer optimization problems, Bayesian analyses, PDEs, and AI training architectures are computationally expensive and inherently intractable problems, that is, $\mathbf{NP}$**-hard** problems (see Fig. 1) [10]; Non-Deterministic ($\mathbf{NP}$) polynomial problems are computational problems where there are no known efficient commonly-used algorithms for finding their solutions in a reasonable polynomial time (i.e. a polynomial number of steps) but can be verified in a polynomial time given their solutions, and $\mathbf{NP}$-$\mathbf{hard}$ problems are computational problems harder than $\mathbf{NP}$ problems. Furthermore, quantum machines harnessing quantum physics phenomena like entanglement can solve some hard problems faster and more efficiently than their counterpart conventional machines ranging from integer optimization problems [11]–[13] to AI techniques [14]–[18] and to PDEs [19], [20], and even quantum-inspired algorithms for solving PDEs [21]. These computational advantages of quantum algorithms (or quantum advantage) over conventional algorithms inspire enough to examine and identify computationally intractable problems with EO methodologies as well as hard EO datasets for near- and far-term quantum machines.

B. DO WE REALLY NEED QUANTUM MACHINES?

Quantum machines can be generally divided into three families, that is, quantum annealers [22], quantum simulators [23], [24], and universal quantum computers [25]. These quantum machines promise computational advantage for computing notoriously difficult problems over conventional computers according to computational complexity theorems/conjectures [26], [27]; computational complexity theorems draw boundaries between computational problems according to their hardness for finding their solutions (see Fig. 1) [10]. At the moment, quantum machines are designed to tackle specific forms and kinds of intractable computational problems, e.g. quantum annealers for Quadratic Unconstrained Binary Optimization (QUBO) problems or simulating the Ising Hamiltonian [11], and quantum simulators for mimicking some physical Hamiltonian [28], [29]. Furthermore, classical computational methods for intractable computational problems reach their limitations and potential accuracy due to the classical computational resource required and the complexity of both EO challenges and datasets. As we stated earlier, some computational techniques are intractable problems on conventional machines and computationally expensive even on the HPC system. The computational methods which are notoriously difficult to compute on a supercomputer but can be tackled efficiently on quantum machines are already proven theoretically and experimentally [30], e.g. for condensed-matter physics and quantum chemistry applications [23], [31]. Condensed-matter and quantum chemistry communities demonstrated the computational advantage of quantum machines over conventional methods such as classical tensor networks (TN) for some of their problems. In particular, research communities ranging from high energy physics [24], condensed-matter physics [29], AI [15] to EO [32] are in the exploration phase of identifying and investigating their hard problems for quantum platforms. Thus, to go beyond current computational methods integrated with large-scale datasets to find a better solution and utilize low computational cost, it is inevitable to examine and identify computationally hard problems in EO applications for novel near- and long-term quantum machines. More importantly, it is vital to gain insight into programming these novel computing machines and their potential advantages and imperfections for computational problems.

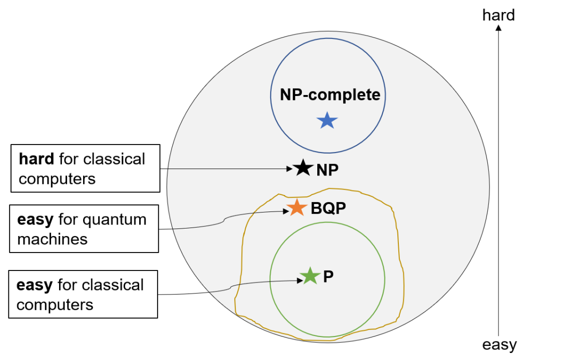

FIGURE 1. The computational complexity conjecture draws boundaries between computational problems according to their hardness based on classical and quantum computational resources required. In particular, the computational problem denoted by the green star is easy to solve for both quantum machines and classical computers, the computational problem denoted by the orange star is easy for quantum machines but hard for classical machines, and the computational problem denoted by the black star is hard for classical computers but no known efficient quantum algorithmic approaches exist for quantum machines.

C. STATE OF THE ART OF QUANTUM COMPUTING FOR EARTH OBSERVATION

Quantum computing is a novel computing paradigm that promises to find solutions to some intractable computational problems more efficiently and faster by exploiting quantum superposition and entanglement than conventional computing techniques if and only if one considers ideal quantum complexity measures without overhead considerations like a distillation of Toffoli gates in the real quantum machines, e.g. the classical versions of the Toffoli gates are transistors in a conventional computer [33]. Quantum machines are a kind of computer constructed using the primitives of a quantum computing method, that is, quantum bits (qubits) and quantum gates in contrast to classical bits and transistors. Universal quantum machines can be decomposed into three layers [34]:

1) a quantum state preparation or a quantum data encoding layer,
2) a quantum unitary evolution or a parametrized quantum gate layer,
3) a quantum measurement layer.

For gaining insight into computing EO problems involving big datasets on quantum machines, there exist already some studies for processing a variety of EO datasets to tackle EO challenges using hybrid classical-quantum approaches (see Fig. 2); hybrid classical-quantum approaches are exchangeable with quantum AI/ML, and a variety of datasets includes hyperspectral, multispectral, and polarimetric EO images. Classification tasks involve satellite images consisting of

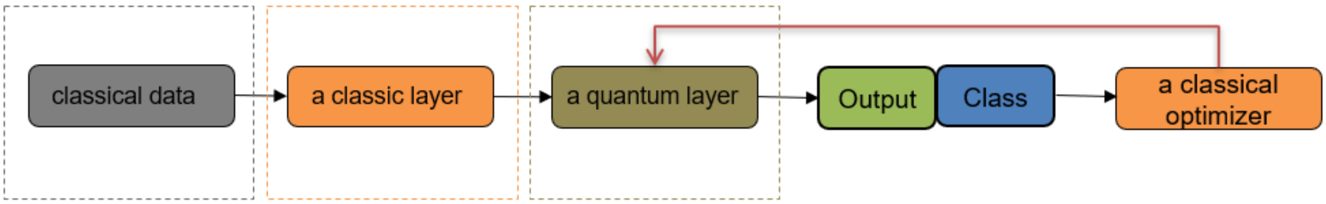

FIGURE 2. A hybrid classical-quantum approach for computational and machine learning tasks. A quantum layer includes implicitly a quantum data encoding layer, a parametrized quantum gate layer, and a quantum measurement layer.

thousands of pixels and hundreds of spectral bands, e.g. Eurosat images having 64×64 pixels and 12 spectral bands [35], while digital quantum machines on the market have less than 100 noisy qubits and a limited depth of faulty quantum gates [36]. Moreover, there is the persistent challenge to embed satellite images in a quantum data encoding layer regardless of the size of quantum machines and their quantum errors. The authors of the article [32], [37]–[40] proposed and utilized a so-called two-level embedding scheme including a classical layer for the dimensionality reduction and a quantum data encoding layer for dimensionally-reduced images, i.e. a hybrid classical-quantum approach, when they used a multispectral Eurosat dataset. Here, a hybrid classical-quantum approach refers to embedding classical datasets in a quantum data encoding layer and optimizing a parametrized quantum gate layer of digital quantum computers with the help of a conventional classical computer. However, the Eurosat dataset is a big dataset comprising low-dimensional and easy-to-classify images, namely, it has a low veracity, while most EO datasets are a small dataset comprising high-dimensional and hard-to-classify images, that is, a with high veracity e.g. a multispectral UC Merced Land Use dataset having 245×245 pixels and 3 spectral bands [41]. Hence, the authors of the article [42] investigated the performance of universal quantum machines having varying depths of a parametrized quantum gate layer when utilizing the multispectral UC Merced Land Use dataset, and polarimetric EO images for naturally embedding them in input qubits without a dimensionality reduction technique [43]. The quality of the given datasets plays an important role in data-driven tasks for hybrid classical-quantum approaches [44]. For instance, the authors of the article [45] analyzed the power of EO image datasets for training universal quantum machines.

Furthermore, a quantum annealer is a kind of quantum simulator being designed to simulate an Ising Hamiltonian equivalent to QUBO problems [22]. The authors of the article [46], [47] analyzed classification problems posed as a QUBO problem belonging to $\mathbf{NP}$-$\mathbf{hard}$ problems on a D-Wave quantum annealer when employing binary and hyperspectral EO images, respectively, since a D-Wave quantum annealer promises to converge to a better solution to $\mathbf{NP}$-$\mathbf{hard}$ problems. A Support Vector Machine (SVM) can also be transformed into a QUBO problem [48]. Hence, the SVM is even optimized on a D-Wave quantum annealer when the authors of the articles [49]–[51] analyzed the EO image datasets. There is even the example of embedding large EO datasets in a D-Wave quantum annealer by using a K-fold technique and the concept of a coreset [52] since a D-Wave quantum annealer has around $5,000$ qubits arranged according to a specifically limited topology. In addition, a D-Wave quantum annealer was proposed for a notoriously hard feature selection task and a multi-label SVM for remotely-sensed hyperspectral images [53].

Inspired by the potential advantage of quantum algorithms, quantum-inspired algorithms are gaining great interest in academia and industry due to their efficiency in power consumption and explainability, e.g. a quantum-inspired quantum Fourier transformation [54], quantum-inspired AI/ML [55], or compressing deep neural networks (DNNs) by using tensor networks [56]. Tensor networks are often designed to compute efficiently quantum many-body systems [57], and they are today extensively utilized to simulate quantum circuits on modern GPU tensor cores [58]. Thanks to these developments, quantum tensor networks are already applied to decrease the number of weights of physics-informed DNNs, and to increase the resolution of hyperspectral images [59].

D. HOW AND WHEN DO QUANTUM MACHINES OUTPERFORM CONVENTIONAL COMPUTERS?

There is a clear indication that quantum processing units (QPUs) will co-exist with conventional classical computers comparable to conventional heterogeneous computing, where one exploits central processing units (CPUs) and general processing units (GPUs). Nowadays, we are in the era of a high-performance computing (HPC) and the quantum computing (QC) paradigm, i.e. novel heterogeneous computing concept which integrates a given CPU+GPU with QPUs. QPUs understand a specific kind and form of computational problems (see Fig. 3); for example, a quantum annealer can be designed to tackle only QUBO problems, and neutral atom platforms for simulating certain chemical Hamiltonians. Moreover, we need to program either an extremely hard heterogeneous computing environment (i.e. CPU+GPU+QPUs) or a conventional heterogeneous computing environment (i.e. CPU+GPU) depending on the level of difficulty of the computational problems.

Digital QPUs (excluding a quantum annealer) currently consist of around 100 error-prone qubits and the low-depth

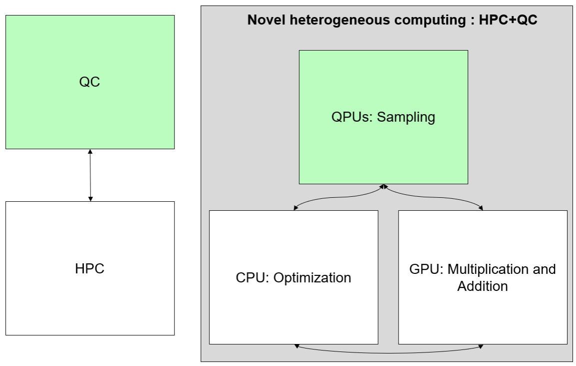

FIGURE 3. Novel heterogeneous computing: a high performance and quantum computing paradigm. Here, conventional heterogeneous computing refers to the programming of both CPU and GPU, whereas we call novel heterogeneous computing when integrating QPUs with CPUs and GPUs. QPUs can be several parallel quantum machines based on different quantum technologies such as quantum annealing, neutral atoms, superconducting, and photonic.

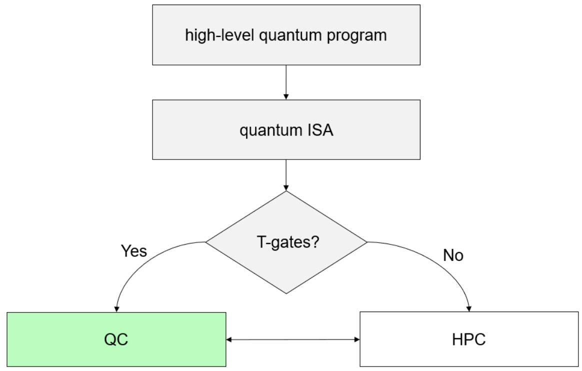

FIGURE 4. Quantum stack for quantum resource estimation. Here, a high-level program is compiled down to a quantum machine code through the quantum ISA. The quantum ISA is the middle interface bridging software and hardware layers.

faulty quantum gates, and the authors of the article [60] coined them “noisy intermediate-scale quantum (NISQ) devices”. For practical computational problems, there is no demonstration yet of the computational advantage of NISQ devices over a conventional classical computer. Toward quantum advantage in EO, it is vital to estimate the quantum resources required for tackling hard computational and machine learning problems, since some quantum algorithms can be simulated efficiently using a conventional classical computer [61], [62]. Thus, any reasonable quantum resource estimation of a quantum algorithm includes, for example, non-Clifford T-gates, error rates of qubits and quantum gates, and the execution time of single- and two-qubit quantum gates. From the perspective of the implementation of a quantum algorithm, non-Clifford T-gates are the most resource-expensive part compared with Clifford quantum gates, that is, CNOT, Hadamard, Phase, and measurement gates. There is even a so-called Gottesmann-Knill theorem which states (informally) that non-Clifford T-gates cannot be efficiently simulated on a conventional classical computer, while Clifford quantum gates can be simulated in a polynomial time using a conventional classical computer without any restriction on entanglement [61], [62]. Namely, quantum algorithms comprising solely Clifford quantum gates can be simulated in $\mathcal{O}(n^2m)$ polynomial steps [63] with n qubits and m Clifford operations, while quantum algorithms consisting of Clifford+T gates take $\mathcal{O}(\kappa t^3\epsilon^{-2})$ exponential steps, where t is the number of T-gates known as T count, a so-called stabilizer state κ growing exponentially $\mathcal{O}(2^t)$, and ϵ the error rate [61]. Some quantum algorithms can also be efficiently simulated using a sophisticated classical technique like a tensor network on GPU tensor cores [64].

A Clifford+T gate set, $\{S, H, \text{CNOT}, T\}$, forms a universal gate set for digital QPUs thanks to its feasibility for quantum error correcting known as a surface code [65]. More importantly, the surface code helps build fault-tolerant digital quantum computers to go beyond NISQ-era computers [36]. In contrast to NISQ computers, fault-tolerant quantum computers are composed of error-free qubits (more than 100) and quantum gates transpiled into the Clifford+T gate set. Hence, this shows that quantum advantage for EO applications can be reached if and only if our quantum learning models have a sufficiently high number $\mathcal{O}(10^{12})$ of T-gates and generalize on unseen data points [66]. Otherwise, we can simulate them efficiently using conventional classical computing resources.

Further, a hybrid classical-quantum approach for computational EO problems is a way of embedding high-dimensional classical data in a limited number of qubits and optimizing the weights of a parameterized quantum model [32], [67]. There is yet another challenging question of how notoriously difficult computational problems can take advantage of both an HPC and QCs, or when should we execute them on an HPC instead of QCs and vice versa? To answer this question, we decompose the parameterized quantum model into the Clifford+T gate set at each learning iteration. If the parameterized quantum model only includes Clifford gates and a small number of T-gates in the quantum Instruction-Set Architecture (quantum ISA) level [68] then we execute it on the HPC instead of the QCs, since we already know that Clifford gates and a few numbers of T-gates can be simulated efficiently using a conventional classical computer (see Fig. 4). The quantum ISA, the quantum version of the conventional ISA, is the interface between software and quantum hardware layers in the quantum stack, and it expresses a high-level quantum program by its surface code. In particular, we re-emphasize that quantum learning models can be simulated efficiently using a classical computer without the need for quantum computers if they do not have a high number of T-gates and do not break the symmetry in their weights (signaling the power of QML models). Therefore, to outperform classical learning models deployed on an HPC system, we should invent and design quantum learning models having thousands of T-gates, and their generalizability on unseen data points is higher than their classical counterparts [16].

Currently, there is (still) no such QML model having hundreds of T-gates and having higher generalizability on unseen data points than its classical counterpart.

II. QUANTUM RESOURCE ESTIMATION FOR HYPERSPECTRAL IMAGES

Instruments on Earth observation satellites detect spectral signals reflected on natural and human-made objects on the Earth's surface, and huge amounts of spectral data in distinct wavelength ranges (Terabytes of data per day) are archived in data storage devices day and night [69]. A hyperspectral imaging satellite, e.g. the EnMAP satellite [70], is an imaging instrument mounted on a satellite for sensing spectral reflectances in ranges of 420 nm to 1000 nm (VNIR) and from 900 nm to 2450 nm (SWIR). Its mission is to collect hyperspectral imaging data to provide vital information for scientific inquiries, societal grand challenges, and key stakeholders and decision-makers relating to

- climate change impact and interventions,
- hazard and risk assessment,
- biodiversity and ecosystem processes, and
- land cover changes and surface processes, to name a few.

For training PQC models on limited benchmark-oriented labeled HSI datasets, we utilized a classical layer for reducing the dimensionality of the features of the HSI datasets due to the limited number of input qubits. However, how much one needs to reduce the dimensionality of the given HSI dataset depends on the quantum computers being utilized, that is, whether we have access to an NISQ device having error-prone qubits ≤ 100 or a fault-tolerant quantum (FTQ) computer having error-free qubits > 100. In particular, the classical machine plays a lesser role in the pre-processing of the HSI dataset, and we can feed many informative features to quantum computers (less dimensionality reduction) as the number of error-free qubits of quantum machines increases. In particular, we assume that we used EnMAP HSIs with 230 spectral bands and 145×145 spatial dimensions, that is, the size of the dataset. Moreover, EnMAP HSIs having $21,205$ data points and 230 features are small-scale image datasets compared with conventional multispectral images for training DL models. To execute the PQC model on NISQ machines having ≤ 100 input qubits, we can either reduce the spectral bands of the EnMAP HSIs from 230 to at most 100 or select the most informative 100 bands to be compatible with the input qubits by utilizing a classical machine. Instead, for FTQ machines having more than 100 logical input qubits, we can persevere more spectral bands of EnMAP HSIs when performing the dimensionality reduction or the feature selection technique in the spectral bands by using a classical machine.

Toward quantum resource estimation, we assessed four different PQC models expressed by the Clifford+T gate set (see Figs. 5-8). The Clifford+T gate set is defined by U_1, U_2,

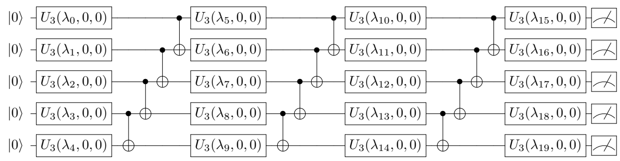

FIGURE 5. A real-amplitude quantum circuit having depth-one is transpiled into the Clifford+T gate set. It is used to demonstrate the power of a PQC model by the authors of the article [16].

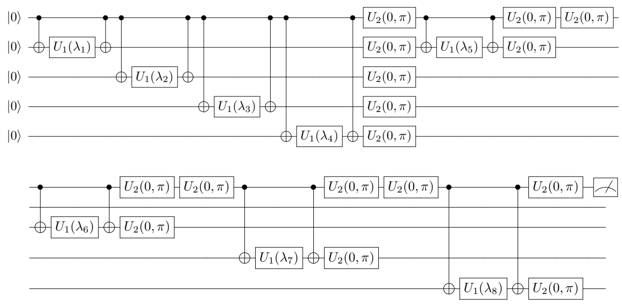

FIGURE 6. An energy-based quantum circuit having depth-one is transpiled into the Clifford+T gate set. This PQC model is proposed for the NISQ device by the authors of the article [71].

U_3 and CNOT gates:

$$U_1(\lambda) = \begin{pmatrix} 1 & 0 \\ 0 & e^{i\lambda} \end{pmatrix}, \quad U_2(\lambda, \phi) = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & -e^{i\phi} \\ e^{i\lambda} & e^{i(\lambda+\phi)} \end{pmatrix},$$
$$U_3(\lambda, \phi, \gamma) = \begin{pmatrix} \cos(\lambda/2) & -e^{i\gamma}\sin(\lambda/2) \\ -e^{i\phi}\sin(\lambda/2) & e^{i(\phi+\gamma)}\cos(\lambda/2) \end{pmatrix}, \tag{1}$$

where, for example, $U_1(\pi/4) = T$, $U_1(\pi/2) = S$, $U_2(0, \pi) = H$. Hence, the Clifford+T gate set is $\{U_1(\pi/2)$, $U_2(0, \pi)$, CNOT, $U_1(\pi/4)\}$. Given an HPC+QC system, the four PQC models shown in Figs. 5-8 comprise several parameterized quantum gates. We can execute them on the HPC instead of the QCs, and the quantum resource required for executing them on QCs is then $\mathcal{O}(1)$ (constant time) if there is either no sign of T-gates or a low number of T-gates. In particular, we will deploy them on either the HPC system or the QCs depending on the existence and the number of T-gates in their configuration during the training phase.

Furthermore, the number of T-gates defines the quantum resource required for deploying QML models on NISQ and FTQ computers. To determine the number of T-gates in our four PQCs, we used the concept of symmetry breaking of conventional neural networks [74]. We strongly emphasize that QML models also break the symmetry in their weights in order to decrease their redundant parameterized quantum gates and they generalize better on unseen data points than with conventional neural networks; namely, each weight within a parameterized quantum layer must have different digital values for capturing unique features. Therefore, we assumed that each layer of the QML models must have at most a single T-gate at each learning iteration, and our QML

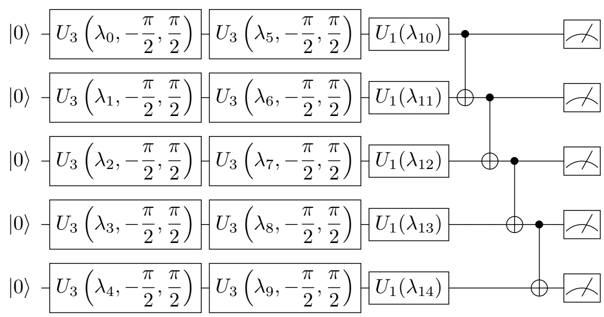

FIGURE 7. A strongly-entangling quantum circuit having depth-one is transpiled into the Clifford+T gate set. This PQC model is proposed to build a powerful quantum learning model in the article [72].

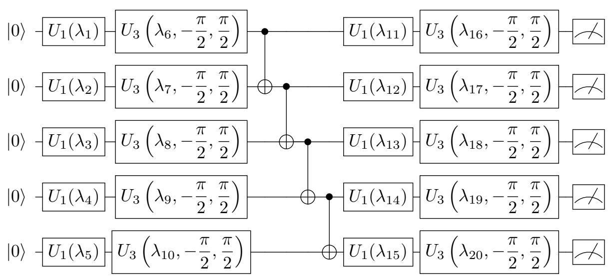

FIGURE 8. A hardware efficient quantum circuit having depth-one is transpiled into the Clifford+T gate set. This PQC is used for quantum variational inference in the article [73].

models having depth-one can only have one T-gate. As for the quantum resource required for executing them on digital QCs [75], we assumed also:

1) If our PQCs have 10^8 T-gates and 5 logical qubits then we need $158,431$ physical qubits (i.e. $9,375$ state distillation qubits, and $149,056$ physical qubits) with a surface code distance of $d = 25$, and our QML models then take around 5 hours.
2) If our PQCs have three T-gates and 5 logical qubits then we need $50,700$ physical qubits (i.e. $14,400$ state distillation qubits, and $36,300$ physical qubits) with a surface code distance of $d = 11$, and our QML models then take around 8.12^{-8} hours.
3) If our PQCs have one T-gate and 5 logical qubits then we need $15,135$ physical qubits (i.e. $14,400$ state distillation qubits, and 735 physical qubits) with a surface code distance of $d = 7$, and our QML models then take around 2.07^{-8} hours.

The quantum resource estimation demonstrates whether the QML models have to be deployed on quantum computers or not [68], [76], and it also generates the number of physical qubits and the depth of a quantum circuit required for deploying quantum algorithms on the surface code quantum computers.

III. CONCLUSION

We assessed the quantum resource required for executing QML models on a digital quantum computer in order to obtain a so-called quantum advantage. We demonstrated that some quantum advantage can only be obtained if and only if QML models have a sufficient number of T-gates and generalize better on unseen data points than their classical counterparts. To count the T-gates of a particular QML model, we used the strong assumption that the QML models must break the symmetry in their weights – identical to the symmetry breaking in conventional deep learning models – so that they become expressively a more powerful model than their counterpart classical learning models. Based on the number of T-gates, we proposed a new HPC+QC paradigm (novel heterogeneous computing) in addition to a hybrid classical-quantum approach. In particular, we can simulate QML models on an HPC system (i.e. CPU+GPU) if they do not have T-gates (or a few T-gates) at the quantum instruction-set architecture level.

Toward quantum advantage in Earth observation, we focused on QML models for hyperspectral images acquired by the EnMAP satellite, since QML models can be trained on a limited labeled dataset, and our HSIs are images with limited label information compared with multispectral images. For QML models, we utilized four parameterized quantum circuits and estimated the quantum resource required for deploying them on digital quantum machines. We found that we can deploy our QML models on an HPC system instead of QCs since they only have a single T-gate due to the symmetry breaking assumption. To design QML models having around $\mathcal{O}(10^8)$ which cannot be executed on an HPC system, they must have almost a depth of $\mathcal{O}(10^8)$, and this is impractical for current and future quantum computers. Toward quantum advantage, it seems, therefore, reasonable to build, first, a special-purpose digital quantum computer for some practically significant computational task instead of a universal digital quantum computer similar to a D-Wave quantum annealer.

As future and ongoing work, we will invent and design a QML model having a reasonable depth, that cannot be simulated on a conventional supercomputer but can be executed efficiently on QCs, and has more expressive power over classical learning models at the same time. We will also design an algorithm for the quantum instruction-set architecture in the quantum software stack. Here, depending on the number of T-gates of a parameterized quantum circuit, the quantum instruction-set architecture decides to deploy a quantum model either on an HPC system or on several QCs comprising a digital quantum computer, and an analog quantum computer.

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