Exploring Image Search on Quantum Computing Systems

Hermann Fürntratt[a], Werner Bailer[b], Florian Krebs[c], Roland Unterberger[d] and Herwig Zeiner[e]
JOANNEUM RESEARCH Forschungsgesellschaft mbH, Graz, Austria
fi

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Abstract: Image search based on descriptor similarities is a fundamental task in computer vision. These descriptors are often highly quantised (e.g. binarised or ternarised). Quantum Computing (QC) has shown to have great potential for a number of tasks including search. Especially Google's new Quantum Processing Unit called **Willow** reaches new milestones in error correction and durability and presents a benchmark that runs about five minutes in the quantum domain while it would take more than 10^{25} years on a state-of-the-art classical supercomputer. The supposed reason that this achievement is not immediately claimed for quantum supremacy is that Google also states that the benchmark — the so called Random Circuit Sampling (RCS) benchmark has "not yet known real-world applications". We therefore transform these benchmark results into the real world by exploring the question: what hardware specifications are needed to execute a quantum implementation of an image descriptor search algorithm more quickly than the fastest supercomputer available today? Hence, two distinct implementations of the Compact Descriptor for Video Applications (CDVA) search, which uses 512-bit descriptors are compared to classical code running on a MI300A unit available in El Capitan, the currently fastest supercomputer with AVX512-bit comands. The results indicate that the current key hardware factors, including gate runtime, coherence time, error rate, and the number of qubits, are still considerably (by orders of magnitude) below the performance levels necessary to compete with the El Capitan supercomputer, but with the recent progress in error correction, we can expect the development of larger quantum systems in the near future that reduces the performance gap between classical and quantum computers. Our source code for simulation is available online at GitHub.

1 INTRODUCTION

Determining the similarity of images is a key aspect of image search applications. A common requirement is to compute a set of similarity scores between one or a few query images and a much larger image database. Depending on the specific application, it may be necessary to identify the best match, the *k*-nearest neighbor matches, or the similarity scores of all images in the database (see Figure 1). In this process, images are typically represented by descriptors — traditionally hand-crafted, but increasingly learned — that are optimised for efficient indexing and matching, often through techniques such as quantisation (e.g. binarisation or ternarisation).

Quantum computing has been shown to have great potential for solving a number of challenging computing problems effectively, and search tasks are among them (Portugal, 2018) (Rieffel and Polak, 2000). We focus on the problem of matching a single binary image descriptor (with size 512 bits) against a database of 100 descriptors in order to obtain a complete list of similarity scores. We assess implementations on two different quantum computing frameworks. Qiskit (IBM) (Research, 2024), which also provides the underlying QASM circuit simulation, and Qrisp (Fraunhofer) (FOKUS, 2024a) as an important framework of the German Qompiler project managed by Fraunhofer FOCUS. It represents Germany's initiative to create a European quantum software development stack. While Qrisp provides higher levels of abstraction (Fürntratt et al., 2024) compared to Qiskit, it still depends on the quantum simulation capabilities of Qiskit.

Quantum algorithms are implemented as circuits, where qubits serve as fundamental information units

[a] https://orcid.org/0000-0002-1762-902X
[b] https://orcid.org/0000-0003-2442-4900
[c] https://orcid.org/0000-0001-5094-5748
[d] https://orcid.org/0000-0002-9165-3749
[e] https://orcid.org/0000-0002-6913-8046

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Figure 1: Example: get k-best keyframe matches depending on their (CDVA) similarity score.

and gates manipulate the state of these qubits. In our exploration, we present two distinct implementation approaches to illustrate different circuit designs. The first approach uses Qiskit, featuring a small number of qubits arranged in a configuration with a large number of gate layers. This setting results in a small but deep circuit (SbD). The second approach uses Qrisp, which allows for a large number of qubits but limits the circuit to a smaller number of gate layers. That setting creates a wide but shallow configuration (WbS). The contrasting implementations allow us to evaluate the performance and efficiency of quantum algorithms under different circuit architectures and provide insights how qubit count and gate depth influence computational capabilities.

In particular, we study under which conditions an algorithm provides the same similarity ranking as exact similarity computation in the classical domain, and the complexity of the quantum implementation depending on the descriptor size.

The main contributions of this paper are:

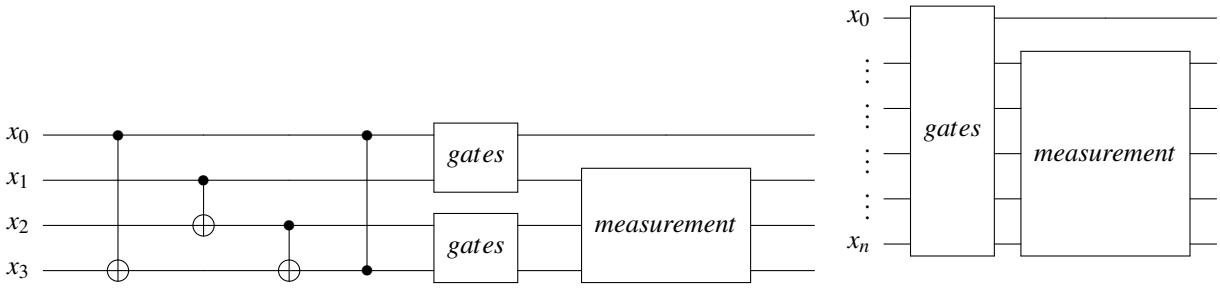
- We show that it is possible to reproduce exact similarity matching results on quantum computers, given a sufficiently high number of *shots* (i.e., runs of the quantum computing algorithms in order to obtain more stable results).
- We demonstrate two fundamental development strategies for quantum computing algorithms, which relate to the number of qubits used on the one hand and the depth of the quantum circuit on the other (small but deep (SbD) vs. wide but shallow (WbS)).
- We calculate the expected performance values based on the Willow quantum hardware specification (AI, 2024b), the qubit count and the gate layer depth and compare them with the expected classical results on El Capitan's AMD CI300A unit (Laboratory, 2025).

The rest of this paper is organised as follows. Section 2 introduces related work on compact descriptors, quantum computing (QC) and frameworks, along with similarity search using QC. Section 3 describes the proposed methods, and Section 4 the setup for the performed experiments. The results are discussed in Section 5, and finally Section 6 concludes the paper.

2 BACKGROUND

2.1 Highly Quantised Multimedia Descriptors

Binarisation or ternarisation of descriptors, in order to perform more efficient indexing and matching, has already been proposed in the era of hand-crafted descriptors. While ternarisation makes handling of descriptors more complex, it has the advantage of discriminating cases where a value of the descriptor vector is (almost) zero and where it has a clear positive or negative value. Well-known examples include BRIEF (Calonder et al., 2011) and BRISK (Leutenegger et al., 2011). A ternary variant of BRIEF, named LTD, has also been proposed (Gao et al., 2013), as well as ternary descriptors for audio tasks (Adnan et al., 2018). Compact descriptors for visual search (Duan et al., 2014) is a standard (ISO/IEC15938, 2019) for image and video description. It includes binary global descriptor components based on hand-crafted and learned feature descriptors. The hand-crafted components contain interest-point based descriptors which are ternarised. A learned descriptor is extracted using the last feature layer of VGG16 (Simonyan and Zisserman, 2015). In order to improve rotation invariance, the descriptor is obtained by applying nested invariance pooling (NIP) (Morere et al., 2017) to rotated versions of the image. This descriptor is then normalised w.r.t. an average descriptor and then binarised. Binarising a network trained for floating point output is suboptimal, thus newer works propose to learn the binarisation as part of the training process. One example is CDbin (Ye et al., 2019), which learns a descriptor using a specific binarisation loss combined with triplet loss for improved discriminability. DBLD (Xiao et al., 2023) is a more recent approach, which proposes a binary transformation layer (BLT) that can be plugged



(a) Small but deep circuit with large number of gates.

(b) Wide but shallow circuit with large number of qubits.

Figure 2: Distinct algorithm design pattern.

into any descriptor extraction backbone.

2.2 Quantum Computing Basics

2.2.1 The Qubit

Quantum computers use quantum mechanical entities such as ions, photons, or atoms as their fundamental information units, known as quantum bits or *qubits* rather than classical bits. While qubits represent the binary states of 0 and 1, similar to classical bits, they can also enter a temporary state of *superposition*. In this superposition phase, a qubit's state becomes non-deterministic and is described by a state vector composed of complex probability amplitudes.

When a system contains m qubits in superposition, the corresponding state vector includes 2^m probability amplitudes, representing all possible combinations of the binary states of the qubits. Each amplitude indicates the likelihood of measuring a specific basis state. For instance, if $m = 3$, the state vector ψ in bra-ket notation (Greenberger et al., 2009) can be expressed as a weighted sum of $2^3 = 8$ basis states:

$$|\psi\rangle = \alpha_{000} \cdot |000\rangle + \alpha_{001} \cdot |001\rangle + \ldots + \alpha_{111} \cdot |111\rangle \quad (1)$$

The term $|\alpha_{000}|^2$ represents the probability of measuring the basis state $|000\rangle$. Quantum operations performed on qubits during superposition manipulate this state vector in parallel, affecting all 2^m entries simultaneously. This ability to operate concurrently highlights the remarkable computational power of quantum computing.

2.2.2 Quantum Gates

The state vector of a qubit system can be altered using quantum gates, which are outlined below. For a more comprehensive explanation, please refer to (Barenco et al., 1995).

Rotation Gates. Rotation gates, (such as the R_Y or R_Z gate), adjust the amplitudes of a qubit by rotating the associated complex coefficient by an angle θ around the specified axis in the complex plane. This allows us to encode classical probabilities $P(V_i)$ of a binary random variable V_i into the angle θ of a qubit by

$$\theta = 2 \cdot tan^{-1} \sqrt{\frac{P(V_i = 1)}{P(V_i = 0)}}. \quad (2)$$

Conditional Gates. At times it is necessary to condition an operation of one qubit on the values of another qubit(s). The Controlled-NOT (CNOT or CX) gate is a two-qubit quantum gate that toggles the state of the second qubit (target qubit) when the first qubit (control qubit) is in state $|1\rangle$. If the control qubit is in state $|0\rangle$, the target qubit remains unchanged.

Multi-Qubit Gates. Multi-qubit gates implement conditioning the operation on one target qubit on several control qubits. For example, an R_Y rotation gate which is controlled by n qubits is denoted as C^nR_Y gate. Similarly, a CNOT gate conditioned on n qubits is denoted as C^nNOT gate. Although many quantum computing frameworks such as Qiskit (Research, 2024) already have implemented such gates, they have to be decomposed (transpiled) internally into elementary gates in order to be executed on a quantum device.

Quantum Algorithms. Quantum algorithms are sequences of quantum gates arranged in circuits and applied to qubits to perform state changes. Because of the probabilistic nature of quantum mechanics, the results of a quantum algorithm are non-deterministic. When measuring the qubits at the end of a quantum circuit, the results will inherently vary each time, even when ran with identical inputs. To solve this is-

sue, quantum computing requires the use of multiple shots.

A *shot* refers to a single execution of a quantum algorithm. After executing the algorithm, the qubit states are measured, and the results are documented. To achieve reliable and statistically significant outcomes from a quantum algorithm, the circuit is usually run multiple times. The results from these shots are then combined to identify the most probable outcome and to estimate the probabilities of various results. Generally, a higher number of shots can lead to longer training times for models and increased costs; however, there are methods available to determine the optimal number of shots with minimal impact on model performance (Phalak and Ghosh, 2023) (Gu et al., 2021).

2.3 Quantum Computing Frameworks

2.3.1 Qiskit

Qiskit is an open-source software development framework for quantum computing created by IBM. The currently available software version v2.0.0 enables users to develop, execute and analyse quantum algorithms on quantum computers and simulators. Qiskit has been designed for a modular structure with different components focusing on various aspects of quantum computing. A foundational layer of Qiskit, providing the tools for the creation of quantum circuits at a low level. It is capable of undertaking tasks such as circuit generation, compilation and optimisation. Users can create quantum circuits, run simulations, and manage the compilation of these circuits for execution on various quantum devices. An additional layer is implemented for simulation of quantum circuits. The software enables users to execute and debug their quantum algorithms on classical computers by simulating quantum operations. It offers high-performance simulators that can replicate the behavior of quantum hardware, allowing users to test and optimise their quantum algorithms before executing them on real quantum devices. Quantum error correction and mitigation is a significant challenge that is also addressed in Qiskit. The framework provides necessary tools to characterise the noise present in quantum devices and to implement the requisite error-correction techniques. The user can perform experiments aimed at understanding and minimising the effects of noise, which is crucial for the reliable computation of quantum data. Qiskit provides tutorials, documentation, and online courses and access to tangible quantum hardware via the IBM Quantum platform[1].

[1]Formerly known as Quantum Experience platform

2.3.2 Qrisp

Qrisp v0.5.10, developed by Fraunhofer FOKUS (FOKUS, 2024b), is a framework designed to bridge the gap between the high-level programming paradigms that characterise modern software engineering and the physical realities of current quantum hardware. The goal of the framework is to provide a unified high-level programming interface as an abstraction to a low-level backend for different hardware platforms. Qrisp is lightweight. The Python framework has user-friendly programming in focus and continues the evolution from pure gate-based quantum programming towards functional programming. With the abstraction of classical data types, e.g. *float*, *bool*, *string*, ..., and programming features such as array-handling and encapsulation, this framework offers a common high-level programming environment with a well-known Python syntax. Qrisp contributes to a more human-readable code with efficient implementations while gate-based code will be hidden underneath.

2.4 Similarity Search Using Quantum Computing

A quantum similarity matching approach for images is proposed in (Liu et al., 2019). It requires a quantum representation of images that cannot be applied to existing descriptors. In another work, a quantum variational autoencoder is used as a feature embedding for satellite imagery in order to perform approximate k-NN search using Hamming distance (Gao et al., 2020), demonstrating significant speedup that can be traded-off against accuracy. A similarity matching approach for proteins models the 20 amino acids described in 5 qubits (Chagneau et al., 2024), and the applied quantum versions of the Needleman–Wunsch and Smith–Waterman algorithms.

An approach for matching a string against a set of sets using the probabilistic quantum memory data structure has been proposed in (Khan and Miranskyy, 2021). For the related problem of edit distance (in particular, edit distance bounded by a maximum value k) a quantum version with complexity $\tilde{O}(\sqrt{nk}+k^2)$ has been proposed[2], and the authors show that this is optimal.

[2]We follow the convention of denoting computational complexity on quantum systems with $\tilde{O}$ in order to discriminate it from the complexity O on conventional computers.

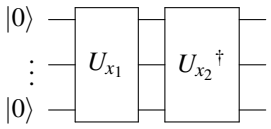


Figure 3: Quantum building block in Qiskit for the Hamming distance estimation with QKE.

2.5 Supercomputing Hardware

As of the latest Top 500 list, the fastest supercomputer is El Capitan, located at the Lawrence Livermore National Laboratory in California, United States. The hardware uses combined 11,039,616 CPU and GPU cores consisting of 43,808 AMD 4^{th} Gen EPYC 24C "Genoa" 24 core @1.8 GHz CPUs (1,051,392 cores) and 43,808 AMD Instinct MI300A GPUs (9,988,224 cores). A single MI300A unit consists of 24 Zen4 based CPU cores, and a CDNA3 based GPU, along with 128 GB of HBM3 memory (Smith, 2025).

The CPUs are capable of processing 512-bit code via the AMD AVX512 command extension, which enhances its performance for data-intensive applications. With a peak performance of more than 2 Exaflops, at a power consumption rate of about 30MW, El Capitan has set new records in various benchmarks, including the High-Performance Linpack (HPL) test (Top500, 2025).

3 METHODS

Under the precondition to work only with real-world data, our quantum algorithm implementations are not yet runnable on real quantum hardware, due to the lack of resources – either the number of available qubits or the limited circuit depth. Therefore we verify our implementations via Qiskit QASM simulation (suitable for less than 32 qubits, i.e. algorithm 1) and – with restricted functionality, as to the best of our knowledge the simulation of 10k+ qubits is only possible with constraints – with the Qrisp default backend simulation (for algorithm 2). We do this on a classical workstation with a 2.1GHz CPU, offering 20 logical cores and 64GB of RAM.

3.1 Algorithm 1: Similarity Search Based on Quantum Kernel Estimation in Qiskit

Based on (Liu et al., 2021), we map a binary n-bit descriptor x_i onto a quantum feature map ϕ

$$x_i \mapsto |\phi(x_i)\rangle \tag{3}$$

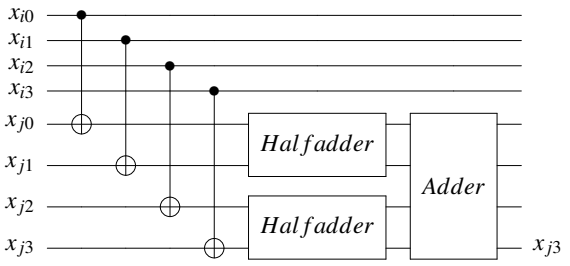


Figure 4: Quantum building block in Qrisp for the Hamming distance with CX gates and adders. The result is available at qubit x_{j3}.

by encoding the n bits of the descriptor into m qubits via

$$|\phi(x_i)\rangle = U(x_i)\,|0^m\rangle \tag{4}$$

with $m = \lceil ld(x_i) \rceil$. Then, the similarity between 2 descriptors x_i and x_j can be estimated by applying an inverted version of x_j, $U^{\dagger}(x_j)$ and estimate the similarity probability $|\langle 0^m|U^{\dagger}(x_j)U(x_i)|0^m\rangle|^2$ by measuring the frequency of the 0^m output. A general circuit layout is depicted at Fig. 3.

3.2 Algorithm 2: Calculate Similarity as Sum of Differences in Qrisp

Based on (Orts et al., 2024), we calculate the similarity between 2 n-bit descriptors as the sum of differences. Furthermore, in contrast to algorithm 1, we assume that hardware scaling issues have been solved and the number of available qubits is by several orders of magnitude higher than at present. Hence, we can map a descriptor bit onto a qubit and use the type system of Qrisp (*QuantumBool*, *QuantumArray*,) along with the Quantum adder modules – especially the *Gidney* quantum adder to calculate the Hamming distance (sum of differences) between two binary descriptors, x_i and x_j. We build a quantum circuit like in Fig. 4 but with a 'function-centred' approach rather than a 'circuit-centred' approach.

Support for pythonic programming paradigms like in the following code snippet facilitates development.

```
# Example for initialising an array
# of QuantumBool from bitstring
a = QuantumArray(QuantumBool(),shape=8)
a[:] = np.fromiter(
[int(bit) for bit in '01010011'], bool)
```

4 EXPERIMENTAL SETUP

We use CDVA (ISO/IEC15938, 2019) descriptors for our experiment, which are extracted from images of the WAVL dataset (Neuschmied and Bailer, 2024)

proposed for landmark retrieval (see Fig. 1). The descriptors consist only of a binary-learned descriptor component, forming a 512-bit vector per image. Real-world data of this size is currently not yet applicable on real quantum hardware. It even poses a remarkable challenge to quantum simulators. Therefore, for experiments with larger descriptors, we briefly outline a way to create these descriptor sizes by concatenating multiple image descriptors. We can think of this as forming a descriptor for a video segment from concatenating subsequent key frame descriptors.

The default similarity metric between a pair of descriptors is the Hamming distance, which can be efficiently implemented on AVX512-capable CPUs like the $4t^{th}$ gen AMD EPYC 24C by counting the set bits (using ASM OpCode *VPOPCNTQ*) in the result of an *VXOR* operation between the inputs.

We obtain a set of similarity scores from matching a single binary image descriptor against a database containing 100 descriptors. In order to obtain more reliable results, we repeat each experiment for 100 randomly sampled descriptors and report the mean of the results (see Tab. 2). We evaluate the implementations by comparing the similarities of a set of descriptors returned by the quantum algorithms to those of the CPU implementation. We do not require the similarity scores to be exactly the same (in particular, in experiments simulating noisy quantum computing operations), but we require the ranking to be the same. Thus we use Spearman's rank correlation ρ as the metric for comparing the outputs of two algorithms. We ignore differences in similarity values, if the absolute difference is smaller than ± 0.5, as in the exact implementation any descriptor difference below 1 would be exactly 0.

We run experiments varying the following conditions:

- Implementation of two fundamentally different similarity search algorithms: algorithm 1, small but deep, and algorithm 2, wide but shallow
- Varying the number of shots. Currently, with an amount of qubits $m \geq 32$ the simulation implementation does not allow to adjust the number of shots (for algorithm 2)
- Varying descriptor length, down to 64-bit in order to get the transpiled CX depth, i.e. the number of layers hosting CX gates (not to be confused with the number of CX gates)

As a consequence of current simulation restrictions, varying the descriptor length beyond 512 bit is planned for future tests, with updated quantum simulators.

5 RESULTS AND DISCUSSION

From (AI, 2024b) we obtain the most important key specs of the Willow Quantum Processing Unit, which consists of two chip units: the first unit is responsible for error correction, while the second unit performs the random circuit sampling benchmark. Since the characteristic values for both chips are distinct, we choose the average of both chip-characteristic values.

These are for the decoherence time t_1 83μs. We calculate the gate runtimes as an average value from the cycle times of the ISWAP gates with 1.1μs and the gate runtimes of 63kHz for a circuit depth of 40, resulting in an average value of 0.75μs, and for the qubit error rates, we also calculate the average of single- and 2-qubit error rates to be 0.14%

For the runtime calculation on the El Capitan CPU, we calculate 1 clock cycle each for the XOR operation of the two descriptors to be compared and also 1 clock cycle for counting the different bit values (VPOPCNTQ) based on the use of the AVX512 unit, which results in a computing time of 1.1×10^{-10}s for determining the Hamming distance of two 512-bit descriptors at a CPU clock frequency of 1.8GHz.

The results related to number of qubits and CX depth show the trade-off between both implementations. Since the CX depth is mainly responsible for execution speed[3], the 1321 extra CX layer for algorithm 1 might slow it down by more than 280% compared to algorithm 2 (see Figure 5). Note that currently, we were not able to evaluate the Qrisp based algorithm on the Qiskit QASM simulator backend (as we did in the Qiskit algorithm case), because the simulator has its maximum qubit number limited to 31 qubits. Therefore, the Qrisp numbers are the results achieved on the Qrisp default backend – which does not apply a noise model and hence retrieves the expected optimal ranking score of 1.0 regardless of the number of shots. In any case, shallow circuit depths promise shorter computing times and thus enable a high number of shots, so that good ranking scores can be expected. Looking at the numbers of shot counts, the value of 5000 shots seems to be a good compromise between speed and ranking quality.

With all assumptions, we calculate that in order to meet the classical calculation requirement of 1.1×10^{-10}s per 512-bit descriptor pair, we need for algorithm 1 using a CX depth of 2042 an average gate runtime lower than 5.39×10^{-14}s and for algorithm 2 with 721 CX gate depth an average gate runtime lower than 1.52×10^{-13}s to become faster than the fastest classical supercomputer.

[3]Credits to R. Seidel from Fraunhofer FOKUS for pointing this out.

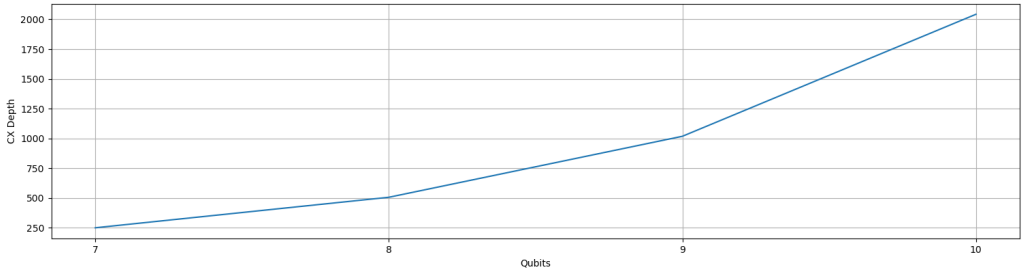


Figure 5: Qiskit algorithm 1: CX circuit depth depending on the number of qubits.

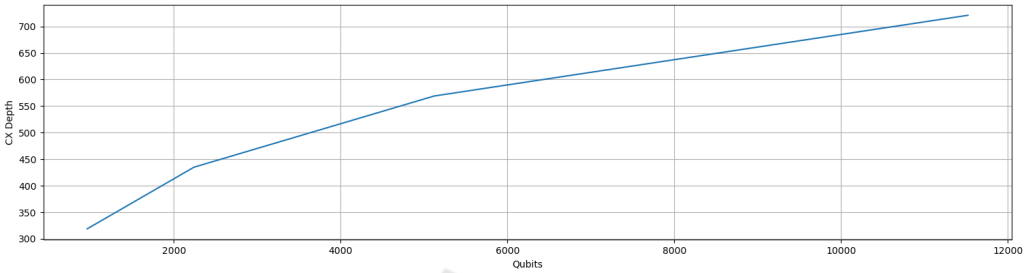


Figure 6: Qrisp algorithm 2: CX circuit depth depending on the number of qubits.

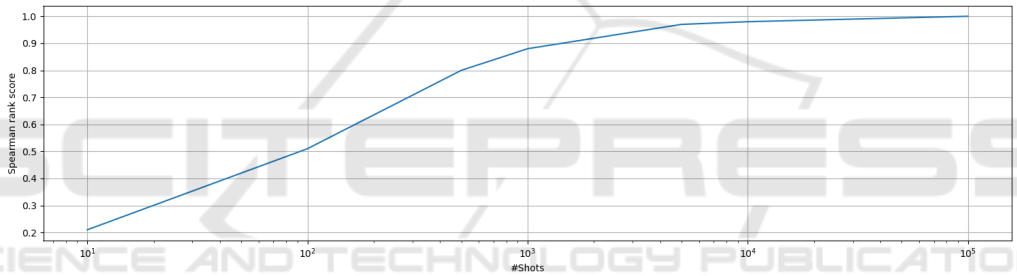


Figure 7: Qiskit algorithm 1: increasing Spearman rank correlation depending on the number of shots.

According to Google's quantum road map (AI, 2024a), the next development goal is to reach 1000 physical qubits. Also in IBM's quantum road map (IBM, 2024), a modular quantum processing unit is expected around 2025, capable to control 7500 gates, which is promising, but the general request for more circuit depth still remains (Chia et al., 2023).

6 CONCLUSION

In conclusion, this paper has explored the potential of similarity searching via descriptor matching on quantum computing systems. We developed two distinct quantum algorithms: one characterised by a limited number of qubits but a deep circuit depth, and the other featuring a larger number of qubits with a shallow circuit depth. Given that the requirements of these algorithms surpass the current capabilities of quantum hardware, we conducted simulations to evaluate matching results on a database of 100 descriptors. These evaluations showed that depending on the number of shots, the baseline results created on classical CPUs are identical.

By making our source code available to the public, we encourage researchers to take this as a starting point for further exploration in this exciting field.

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Table 1: Comparison of the implemented similarity search algorithms.

	Qiskit		Qrisp	
Descriptor	#Qubits	CX Depth	#Qubits	CX Depth
64	7	250	961	319
128	8	506	2241	435
256	9	1018	5121	569
512	10	2042	11521	721

Table 2: Comparison: Spearman rank correlation over 100 512-bit descriptors depending on number of shots.

	Qiskit			Qrisp		
#Shots	Avg	Min	Max	Avg	Min	Max
10	*0.21*	-0.07	0.51	1.0	1.0	1.0
100	*0.51*	0.28	0.69	1.0	1.0	1.0
500	*0.80*	0.66	0.90	1.0	1.0	1.0
1000	*0.88*	0.77	0.94	1.0	1.0	1.0
5000	*0.97*	0.93	0.99	1.0	1.0	1.0
10000	*0.98*	0.96	0.99	1.0	1.0	1.0
100000	*1.00*	0.99	1.00	1.0	1.0	1.0

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