Final report summary

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Titolo prova finale: Classification with Hybrid Quantum-Classical Neural Network
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Machine Learning, by which machines get better in performing a task acting on data, has given important results and solved different problems, both in science and in our daily life. An example is represented by voice recognition and targeted advertising. *Neural networks* were developed to simulate the human nervous system for machine learning tasks. At the beginning of XXI century, greater data availability and increasing computational power led to increased success of this model and of *Deep Learning*; thanks to mathematical models and statistical algorithms, learning process occurs automatically. In some cases the results of artificial intelligence reached and outperformed human's ones for example in image recognition. Neural networks are *theoretically* capable of learning any mathematical function with sufficient training data, and in some cases they are known to be *Turing complete*. The problem may be represented by the amount of data required for learning process, which causes a corresponding increase in training time. New and more powerful paradigms such as *Quantum computing* may be necessary.

Quantum computers exploit quantum mechanical proprieties of matter, such as *iterference*, *entanglement* and *superposition* of states in order to perform calculation. As well as information and data are stored in bits (0 or 1) in classical computers, quantum computers use *qubits* which can be found in superposition of states taking *continuous* values. As a consequence of this feature, some problems may be solved faster on quantum computers than on classical ones. In 2019, Google laid claim to *quantum supremacy* having solved a computational task on a quantum computer with a remarkable gain of time. Moreover, as logic gates perform operations over classical bits, *quantum gates* can transform qubits in a quantum circuit in a reversible way.
There are several models of quantum computers, such as *Quantum Turing Machines*, *Adiabatic Quantum Computing* and *Quantum Circuits*, which is the most popular one, and many private companies are currently developing their quantum components. Research is focused both on algorithms that may be run on quantum computers and on technological aspects, studying physics of matter in order to exploit its quantum properties. Several studies are made in order to find the best applicable solution, using *superconductors*, *trapped ions* or *topological qubits*. NISQ (noisy intermediate-scale quantum) devices, despite being limited in the number of quibts and subject to noise, are supposed to give benefits in various disciplines in the near term future.

The prospects of reducing computational time and data dimension through the use of quantum computers led to *Quantum Machine Learning*. Despite being state-of-art research, many ideas have been developed that may bring benefits in different situations. To set an example, *Quantum annealers*, which find the low energy state of a system, may perform some optimization tasks in shorter time. Hybrid quantum-classical algorithms, where some computation is made classically and some on quantum machines, are expected to outperform classical algorithms in the near future. Hybrid neural networks may be found in this context: these tecnhologies are based on parametrized circuits to be optimized for classification tasks. The most common form for this model is based on two main components: a function which aim is to embed classical data into a quantum computer and a variational function with some free parameters to be optimized.

In this thesis project a particular implementation of hybrid neural networks is studied. The aim is to perform image recognition, MNIST digit, in a *Supervised Machine Learning* context, where information about data is known. A hidden layer of a classical neural network is implemented using a parametrized quantum circuit. The outputs from the previous layer are collected and used as inputs for the circuit. The measurement statistics of the quantum circuit can then be collected and used as inputs for the following layer. In the end, the outputs of the neural network are numerically compared with the expected results through a loss function, defined as in the classical case. The parameters in our quantum circuit and the ones in the classical layers are optimized through the *backpropagation* algorithm, where the optimization process is implemeted in order to be compatible with the quantum circuit via the *parameter shift rule*. The aim is to minimize the loss function and to find a model being able to predict correctly the features of our input data. Programs have been implemented in Python coding language through *Qiskit* and *Pytorch*, Python libraries used for *Quantum Computing* and *Machine Learning* respectively. Then, the programs have been tested both on simulators and on actual quantum computers on the online platform *IBM Quantum Experience*, that gives the opportunity to run programs on the IBM quantum computers.

Several experiments have been carried out starting from the previous model, changing the circuit features and the number of its qubits. Moreover, gaussian errors with different standard deviation values have been added to our validation set of data, in order to test our model for the better, and also to our training data, to make it stonger. Specifically, three-dimension rotation, U3 gate, has been used for a single qubit circuit, which led to 99.9% accuracy both on simulator and on actual quantum devices. Furthermore interesting results have been obtained for the noisy validation data in this experiment with an accuracy higher than 99% up to 0.7 deviation standard value. Then, more-qubits circuit was used, where parametrized rotations act on each qubit, which gave an accuracy of 99% for non-noisy validation data and interesting results for noisy validation data when learning was made with noisy data too. In the end, other two circuits were tested: entangled qubits circuit and a circuit inspired by a hybrid optimization algorithm, QAOA, which still makes use of entanglement. In these cases, the resultant accuracy value was of 99% and of 98% respectively on the quantum devices.

The thesis is divided into three chapters:

1. In the first chapter the theoretical features of Machine Learning and Quantum Computers are analysed, focusing on the aspects that have been used for the thesis project.

2. The first part of the second chapter is dedicated to an overiew of Quantum Machine Learning. Then, the technical features of the implemented programs are presented and the held experiments are described.

3. The third chapter is dedicated to crytical analysis of obtained results, the possible future implementations of the model and conclusions.