# MNIST Classification with Quantum Phase Estimation

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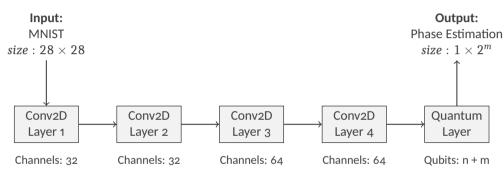
04/23/2025





#### **Neural Network**

1 Introduction



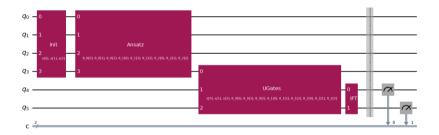
The Conv2D layers extract features from images and build their embedding to pass to the quantum layer.



### **Quantum Layer structure**

2 Quantum Layer

The final quantum layer is made of four main blocks:

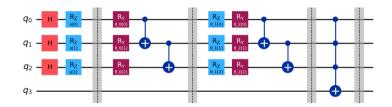




### **Initialization + Ansatz**

2 Quantum Layer

It is made of *n* qubits and has the below architecture:



The number of iterations ( $R_z + R_\gamma$  gates on each qubit) can be arbitrary set. The state on the last qubit can be written as:

$$|\psi>=a|1>+b|0>$$
 (1)



In order to apply the QPE, it is crucial to build a unitary gate such that:

$$U|\psi> = e^{-i2\pi\phi}|\psi> \tag{2}$$

$$U=V\Lambda V^{\dagger}$$
 where  $V=egin{bmatrix} b&-a^*\ a&b^* \end{bmatrix},$   $\Lambda=egin{bmatrix} e^{-i2\pi\phi}&0\ 0&e^{i2\pi\phi} \end{bmatrix}$  (3)

$$U = \begin{bmatrix} \cos(2\pi\phi) - ic\sin(2\pi\phi) & 2ia^*b\sin(2\pi\phi) \\ 2iab^*\sin(2\pi\phi) & \cos(2\pi\phi) + ic\sin(2\pi\phi) \end{bmatrix}, \quad c = |b|^2 - |a|^2 = \frac{2^m - 2}{2^m}$$
(4)



U can be written as a composition of standard gates,  $R_z + U_3$ :

$$U = U_3 R_z = \begin{bmatrix} e^{-i\alpha} \cos \theta & -e^{i(\alpha+\lambda)} \sin \theta \\ e^{i(\beta-\alpha)} \sin \theta & e^{i(\alpha+\beta+\lambda)} \cos \theta \end{bmatrix}$$
 (5)

Comparing equations 4 and 5, all the angles can be written as:

$$\alpha = \arctan\left[c\tan(2\pi\phi)\right], \quad \theta = \arccos\left(\frac{\cos(2\pi\phi)}{\cos\alpha}\right)$$

$$\lambda = -\alpha + \arctan(\cot\phi), \quad \beta = -\lambda$$
(6)



#### **U** Gate

#### 2 Quantum Layer

Knowing U allows us to build the UGate block; it is made of m qubits.



An arbitrary function can be chosen for the global phase  $\psi$ . Here:

$$\phi = \sum_{\text{weights}} \omega_i^2 + \sum_{\text{inputs}} x_i^2 \tag{7}$$



At the end of the circuit, a IFT gate is applied to measure the global phase  $\phi$ . This gate produces a state (on the last m qubits) of the form:

$$|\psi_{IFT}\rangle = \sum_{\mathbf{x}} \alpha_{\mathbf{x}} |\mathbf{x}\rangle \quad \text{where} \quad \alpha_{\mathbf{x}} = \frac{1}{2^m} \sum_{k} e^{-i2\pi k(\phi - \phi_{\mathbf{x}})}$$
 (8)

The probability of measuring a state |x> is then:

$$P_{x} = \frac{1}{2^{2m}} \left( \frac{\sin(2^{m}\pi(\phi - \phi_{x}))}{\sin(\pi(\phi - \phi_{x}))} \right)^{2}$$

$$\tag{9}$$



### **Training losses**

3 Training

The network is trained in two different steps:

• Triplet-loss:

$$L_T = \sum_{inputs} \max \left[ 0, d(anchor, pos) - d(anchor, neg) + margin \right] + \lambda \Omega$$
 (10)

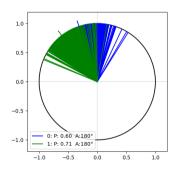
where d is the KL-divergence and  $\Omega = -\min_{i \neq j} ||c_i - c_j||^2$ .

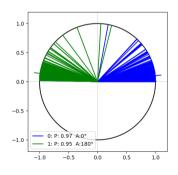
CrossEntropy loss:

$$L_{\mathcal{C}} = -\sum_{i} \ln(x_{i}[argmax(x_{i})]) \tag{11}$$



## O-1 Digits 4 Results

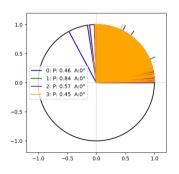


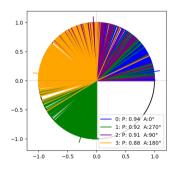


- qubits for eval: 7
- qubits for pe: 1
- iterations: 5
- Train-set length: 1200
- Accuracy: 0.998



# O-3 Digits 4 Results

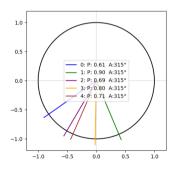


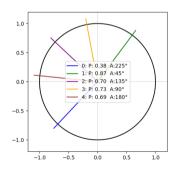


- qubits for eval: 7
- qubits for pe: 2
- iterations: 5
- Train-set: 1200
- **Accuracy:** 0.985



## O-4 Digits 4 Results

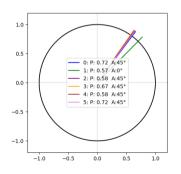


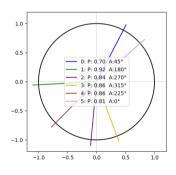


- qubits for eval: 7
- qubits for pe: 3
- iterations: 5
- Train-set: 6000
- Accuracy: 0.920



## O-5 Digits 4 Results

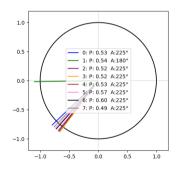


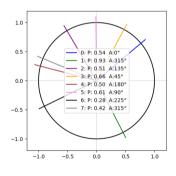


- qubits for eval: 7
- qubits for pe: 3
- iterations: 5
- Train-set: 15000
- Accuracy: 0.907



## O-7 Digits 4 Results





- qubits for eval: 7
- qubits for pe: 3
- iterations: 5
- Train-set: 33600
- Accuracy: 0.601