# Quantum Convolutional Neural Networks for Binary Classification

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***Abstract*—We present a quantum convolutional neural network (QCNN) as a solution for binary classification tasks with limited training data. We have achieved a high accuracy just by using 10 samples of the Iris plant dataset. We also investigate the effects of different quantum data embedding techniques on the model's performance.**

## I. Introduction

The Convolutional Neural Network (CNN), inspired by the visual perception mechanisms of living organisms, is one of the most well-known machine learning models for classification tasks. CNN has frequently been applied to binary classification [1], [2]. However, they all deal with a similar concern: they require a large amount of training data to achieve the highest accuracy. A Quantum Convolutional Neural Network (QCNN) is an alternative approach to this problem due to its ability to train with fewer data [3]. In this work, we examined the applicability of QCNN for binary classification using a small set of training data. Furthermore, we observe how data embedding techniques affect the model's accuracy and losses.

## II. Method

This section outlines our QCNN model for binary classification.

### A. Quantum Convolutional Neural Network

There are two types of layers that are applied repeatedly in an alternating manner, as shown in figure 1. We build a convolutional and pooling layer for a quantum circuit using the QCNN framework from [4]. The convolutional layer should use updated two-qubit unitary weights. We express this arbitrary two-qubit unitary with a sequence of gates: two single-qubit U3 gates (parametrized by three parameters each), three Ising interactions (each parameterized), and two more U3 gates on each qubit. In this situation, the pooling layer inputs are the weights of single-qubit U3 gates. Then, we apply conditional measurements to half of the unmeasured wires, halving the system's size.

### B. Datasets

From the classical Iris plant dataset, we will classify two of the three Iris species (*Iris-Setosa* and *Iris-Versicolor*). We used sets of 2, 5, 10, 20, 30, 40, and 50 of the 100 data points in our experiment as training data and the remaining 50 as validation data.

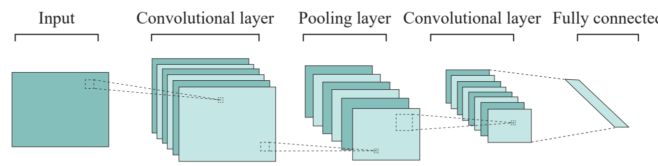


Figure 1: Illustration of CNN architecture.

### C. Quantum Data Embedding Methods

We use amplitude embedding and angle embedding to do this work. Amplitude embedding encodes a real or complex-valued $M$-dimensional classical data point $x$ into amplitudes of a $m$-qubit quantum state

$$|\psi_{\mathbf{x}}\rangle = \sum_{i=0}^{M-1} x_i |i\rangle, \tag{1}$$

where $M = 2^m$, $x_i$ is the $i$-th element of $x$, and $|i\rangle$ is the $i$-th computational basis state. The main benefit of amplitude encoding is that we only need $m = \log M$ qubits to encode an input with $M$ features and $m = \log(NM)$ qubits if we have $N$ of those inputs. Nevertheless, it is known that the depth of a state preparation circuit employing amplitude embedding is $2^n$ parallel operations, most of which are expensive 2-qubit gates. [5]. The amplitude embedding was already used in [3], so we want to compare it to the angle embedding.

We use rotation X gate for angle embedding which is stores the $N$ classical features into the angle of rotation along with X axis of the $n$ qubits

$$|\psi_{\mathbf{x}}\rangle = \bigotimes_{i}^{n} R_X(x_i)\,|0^n\rangle, \tag{2}$$

where $R_X$ is rotation $X$ gate. Although angle embedding can prepare a state with relatively few operations, it is not the most effective method for the required qubits. As there are only four features in the iris plant dataset, we only need four qubits for angle embedding and two for amplitude embedding. However, to generate 2-layer QCNN, we need at least 5 qubits. Then we need to add 28 normalized zeros to our dataset.

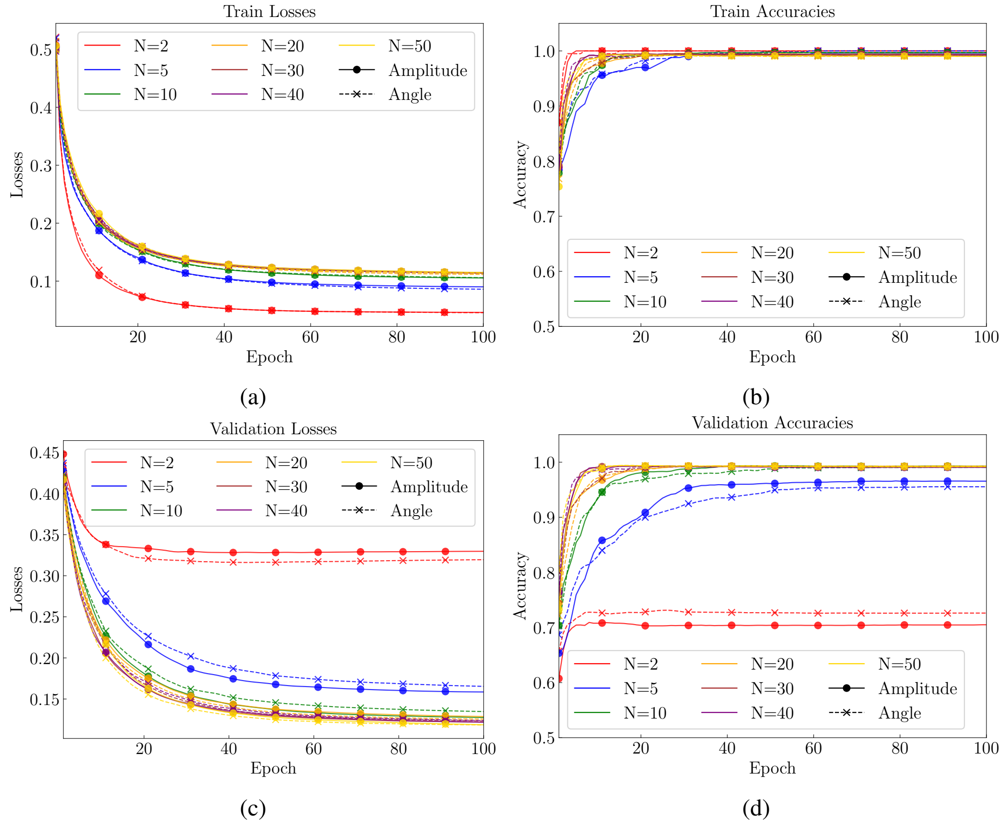


Figure 2: Train losses (a), train accuracies (b), validation losses (c), and validation accuracies (d) for each training data size ($N$) along with the epochs. A dot and a straight line represent the result of amplitude embedding, whereas a cross and a dashed line represent the result of rotation X angle embedding.

## III. Result

We use 2-layer QCNN and then train our model with 100 epochs for each embedding technique. For updating the circuit's parameters, we use an ADAM optimizer. We iterate our experiment 100 times and then calculate the mean for losses and accuracies. The result of our experiment is depicted in figure 2. As seen in the figure, there is no significant difference between amplitude embedding and angle embedding in losses and accuracies. Train accuracy for each amplitude embedding and angle embedding can converge to 100% with less than 10 epochs for each training data size. However, the validation accuracy will be higher when $N \geq 10$.

## IV. Conclusion

We trained the quantum convolutional neural network (QCNN) to distinguish between *Iris-Setosa* and *Iris-Versicolour*. With a minimum of 10 samples and 100 training epochs, we have achieved a model with nearly 100% training accuracy. There does not appear to be a significant difference between amplitude embedding and angle embedding with rotation X in terms of losses and accuracies for binary classification. However, the efficiency of qubits and operations can be a factor in determining which embedding technique is appropriate for certain tasks and datasets.

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