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# A Quantum Approach to Neural Networks

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**Abstract:** *Artificial neural networks, usually just called neural networks, computing systems indefinitely inspired by the biological neural networks and they are extensive in both research as well as industry. It is critical to design quantum Neural Networks for complete quantum learning tasks. In this project, we suggest a computational neural network model based on principles of quantum mechanics which form a quantum feed-forward neural network proficient in universal quantum computation. This structure takes input from one layer of qubits and drives that input onto another layer of qubits. This layer of qubits evaluates this information and drives on the output to the next layer. Eventually, the path leads to the final layer of qubits. The layers do not have to be of the same breadth, meaning they need not have the same number of qubits as the layer before and/or after it. This assembly is trained on which path to take identical to classical ANN. The intended project can be compiled by the subsequent points provided here:*

*1. The expert training of the quantum neural network utilizing the fidelity as a cost function, providing both conventional and efficient quantum implementations.*

*2. Use of methods that enable quick optimization with reduced memory requirements.*

*3. Benchmarking our proposal for the quantum task of learning an unknown unitary and find extraordinary generality and a remarkable sturdiness to noisy training data.*

**Keywords**: Quantum Computing, Artificial Neural Network, Quantum Neural Network

## I. Introduction

The concept of artificial neural networks has been proposed around the 1950s mainly to mimic the different activities of the human brain. an artificial neural network (ANN) Over the ages, quantum computing has witnessed outstanding development which has a great impact on accelerated computing. Related to the artificial neural network (ANN), an unprecedented, beneficial, and applicable concept has been intimated which is known as a quantum neural network (QNN). [5][20]

QNN has been realised combining the rudiments of ANN with a quantum computation standard which is superior to the traditional ANN[8]. Quantum computers assure notable advantages over classical computers for several different applications. A quantum computer harnesses some of the mystical marvels of quantum mechanics to achieve gigantic bounds forward in processing power. Quantum machines guarantee to outstrip even the most capable of today—and tomorrow—supercomputers. Machine learning (ML), especially applied to deep neural networks via the back propagation algorithm, has permitted a wide range of innovative applications extending from the social to the scientific.

Regardless of quick theoretical and solid progress, ML training algorithms are computationally expensive and, now that Moore's law is stumbling[7], we must contemplate a future with a more delayed rate of advance.

Furthermore, the purpose of QNN may also be seen in some of the related research papers. As such, this paper covers different types which have been Set and further the implementation of the equivalent in many applications. To concede the powerfulness of QNN, a several results and approaches are included to show that these new models are more relevant and effective than traditional ANN. Discovering a suitable set of weights for a neural network has become one of the most studied problems of modern machine learning. It has presented a significant challenge to computer scientists for whom few successful alternatives to back-propagation are available. It can be difficult to explore very large search spaces efficiently and, worse, optimization may converge to a local minimum far from the global optimum.

### 1.1 Basic Quantum Concepts

Quantum bits are the fundamental units of information in quantum information processing in much the same way that bits are the fundamental components of information for classical processing. the space of possible polarization states of a photon is an example of a quantum bit or qubit. A qubit has a continuum of possible values: any state represented by a unit vector a |↑⟩ + b |→⟩ is a legitimate qubit value. the amplitudes a and b can be complex numbers, even though complex amplitudes were not needed for the explanation of the experiment. (In the photon polarization case, the imaginary coefficients correspond to circular polarization.)Overall, the state space of the system is the set of all conceivable states of a physical system. Any quantum system that can be modelled by a two-dimensional complex.

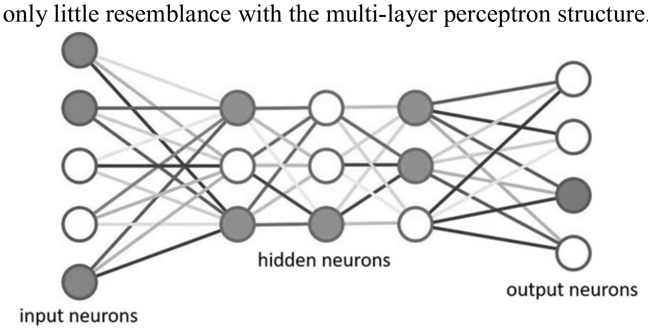
Vector space can be viewed as a qubit. the two-state type for these methods does not mean that the state space has just two states but it has especially many—but rather that all feasible states can be expressed as a linear aggregate, or superposition, of only two states Paul Dirac's bracket symbol, is used everywhere in quantum physics to express quantum states and their transformations. the notation |.>, <.| j is called ''Dirac notation'', given after the name of renowned theoretical physicist Paul Dirac is mainly used in quantum computation, which embodies the standard notation for the states in quantum mechanics. <.| is a bra vector which is a complex conjugate transpose of ket vector and it represents a row vector and |.> i is a ket vector which is commonly a column vector. If we determine a matrix with a ket vector, we get a ket vector again. Synchronically bra and ket produce an inner product that is pooling together <x| and |y> as <x|y> denotes an inner product of two vectors which always yields a scalar quantity.

Quantum computing is based on quantum bits (or qubits) following the rules of quantum physics as opposed to the traditional bits of today that are based on traditional physics. Since Moore's law meets its demise, two brand-new computing paradigms have been found, neuromorphic and quantum computers. Note that in physics the term classical/traditional is used to determine non-quantum and we obtain use of this nomenclature throughout. Quantum machine learning strives to find an improvement in employing quantum computing in machine learning. The current study into QML falls into one of two classes[7] Some quantum algorithms promise innovation in machine learning in theory but contain many gaps in their implementation in practice. In contradiction, others are more realistic in their method, but scuffle to prove a place amongst the well-established techniques of machine learning.

In this proposal, it is explained that a quantum computer can output a quantum state that incorporates the entire cost landscape for a given neural network. The method is shown to be adaptable and has some remarkable properties, as the ability to generalize from very small data sets and a remarkable resiliency to noisy training data[10cal]

## II. Literature Review

To explain a variety of ideas, ranging from quantum computers imitate exact computations of neural nets, to general trainable quantum that bear only little resemblance with the multi-layer perceptron structure.




Already in the 1990s, quantum scientists have tried to arise with different quantum versions of recurrent and feed-forward neural networks. The models were attempts to change the modular edifice and also the nonlinear activation ideas of neural networks into the language of quantum algorithms. However, one could claim that series of linear and nonlinear calculations are rather "unnatural" for quantum computers.[10] More recent research has tackled this dilemma, special estimation designs or changes of the neural nets that make them more responsive to quantum computing, but the advantages of these designs for machine training are still not conclusively established.[2]

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As a preparation method, it has important changes as it is landscape-independent, has a quadratic speedup above a regular search of same kind, and would be able to discover statistically vague problems such as parity problems

## III. Aim, Objective and Outcome

We have introduced a quantum analogue from formal neurons, which provide a quantum feed forward neural network skilled in universal quantum estimation[21]. Calculating fidelity as a cost function which is employed by both the tradicitonal and efficient quantum implementations. Memory requirements are significantly reduced and our proposal offers more accelerated optimization: the number of qubits needed scales with only the width, conceding deep-network optimization. [7][24] We measure the efficiency of our proposal for the quantum task of learning an undiagnosed unitary and find excellent generalization behaviour and striking resiliency to noisy training data.

To build a completely quantum extensive neural network competent in universal quantum computation we have found it important to change the existing proposals. A quantum perceptron to be a common unitary executive acting on the corresponding input and output qubits has been defined by us, whose parameters incorporate the weights and biases of past proposals in a complex way. Moreover, we introduce a practice algorithm for this quantum neural network that is effective in a way that it only relies on the breadth of the individual layers and not on the depth of the network..We notice that the proposed network has some remarkable properties, as the capability to generalize from very small data sets and a remarkable susceptibility to noisy training data.

## IV. Scope

### 4.1 Justification

A series of barriers faced by the author of a QML algorithm for quantum data includes obtaining the right quantum generalization of the perceptron, (deep) neural network structure, optimization algorithm, and loss function.In this paper, we face these difficulties and offer a natural quantum perceptron that, when combined into a quantum neural network (QNN), is proficient of carrying out the universal quantum computation[10]. By utilising completely the positive layer transition maps our QNN design allows for a quantum analog of the standard backpropagation algorithm . We employ our QNN to the task of studying an unfamiliar unitary, both including and excluding errors. Our classical simulation results are very promising and urge the practicability of our system for noisy intermediate scale (NISQ) quantum devices[23]

In this paper, we define a quantum perceptron to be a customary unitary operator acting on the identical input qubits and output qubits, whose parameters include the weights and biases of previous proposals in a simple way. Moreover, we introduce a training algorithm for this quantum neural network that is effective in the sense that it only depends on the width of the unique layers and not on the depth of the network. It is also an essential consideration that there is no aspect of exponentially disappearing gradients insufficiently expressive parametrized quantum circuits .. in the cost function landscape. We find that the proposed network has some exceptional properties, as the ability to hypothesize from very small data sets and a remarkable understanding to noisy training data sets[17]

### 4.2 Product Scope Description

#### A. The Network Architecture

The most modest structure block of a quantum neural network is the quantum perceptron, the quantum analog of perceptrons used in traditional machine learning. In our proposal, a quantum perceptron is an imperious unitary executive with m input qubits and n allowing qubits. Our perceptron is then readily an imperative unitary suited to the m + n input and output qubits which depend on $(2m+n)2-1(2m+n)2-1$ parameters. the input qubits are initialized in a likely unknown mixed state $\rho$in and the output qubits in a fiducial output

state $|0\cdots0\rangle$out$|0\cdots0\rangle$out (note that this scheme can easily be progressed to qudits).

For clearness in the following, we focus on the matter wherever our perceptrons act

on m input qubits and one output qubit, i.e., they are $(m + 1)$-qubit unitaries

Now we have a quantum neuron that can express our quantum neural network architecture. With the formal case and sequential operational plans we propose that a QNN is a quantum pathway of quantum perceptrons organized into L hidden layers of qubits, obeying on an initial state of the input qubits, and producing an, in customary diverse state for the output qubits according to

Pout ≡ trin,hid (μ(P ⊗ |0···0⟩hid,out <0···0|)μ†

Where,

U ≡ UoutULUL−1···U1 is the QNN quantum circuit,

Ul is the layer unitaries, comprised of a product of quantum perceptrons acting on the qubits in layers l − 1 and l.

It is essential to note that, because our perceptrons are arbitrary unitary operators, they don't usually commute, so that the order of operations is meaningful.

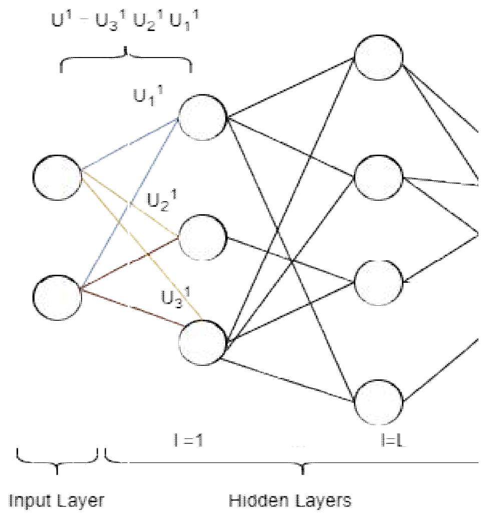


**Figure 2:** Feed Forward QNN architecture

A quantum neural network has input, output, and L hidden layers. We apply the perceptron unitaries layer-wise from top to bottom (indicated with colors for the first layer): first the violet unitary is applied, followed by the orange one, and finally the yellow one.

### 4.3 Acceptance criteria

The cost function takes a slightly more complicated form when the training data output states are not pure, which may occur if we were to train our network to learn a quantum channel. the cost function varies between 0 (worst) and 1 (best).

### 4.4 Deliverables

- To minimize cost function for QNN
- Achieve generalization of the quantum neural network against noisy (random) pairs and evaluate corresponding cost function for it.
- Once generalized, check the robustness of QNN to noisy data.

### 4.5 Assumptions

- A qubit cannot be copied like a classical bit
- The computer has high-performance GPU such as NVIDIA 1080TI
- The quantum computing library has density matrices and ket states for quantum operations.
- The computer has dedicated RAM for training the QNN.

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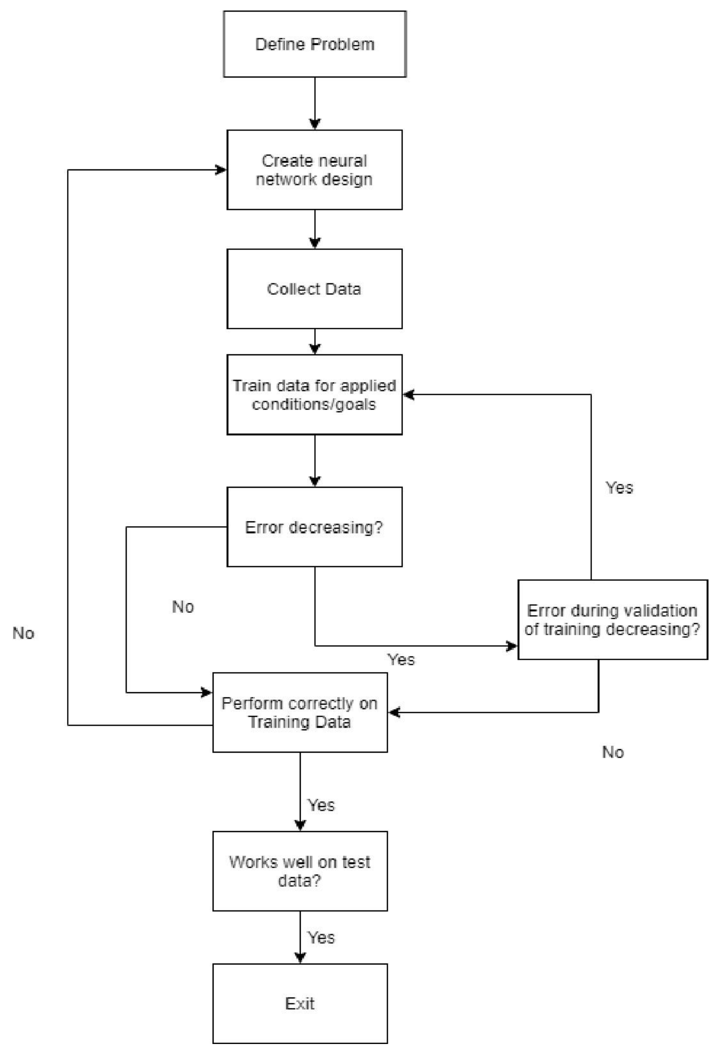
## V. Proposed System

### 5.1 Details of Hardware & Software

| Details of Hardware and Software | |
|---|---|
| Hardware Requirements | IBM Quantum Computer - 16 GB RAM |
| Software Requirements | Python-3x scipy,qupit,time,random,matplotlib.pyplot |
| Technology Used | NeuralNetwork, Quantum Computing |

### 5.2 Design details

#### 5.2.1 Flowchart



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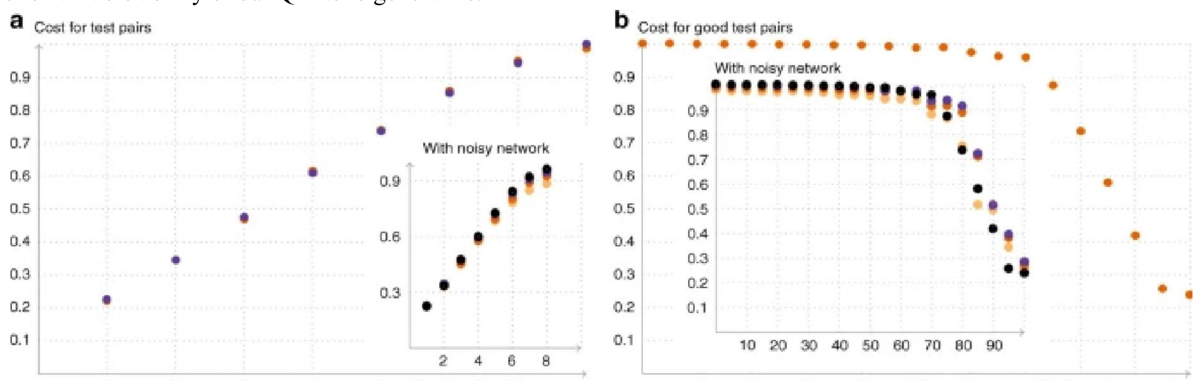
### 5.2.2 Simulation

To assess the performance of our algorithm we have thus been reduced to QNNs with small widths. It's pointless to simulate and Train deep QNN learning algorithms for more than a handful of qubits Carrying out pilot simulations for I/O spaces of m = 2 and 3 qubits and have examined the behavior of the QML gradient descent algorithm for the task of learning a random unitary V.We focussed on two separate tasks: In the first task, we studied the ability of a QNN to generalize from a confined set of random training pairs (||ϕinx⟩, V||ϕinx⟩)(|ϕxin⟩, V|ϕxin⟩), with x = 1,…, N, where N was smaller than the Hilbert space dimension. the results are displayed. Here we have outlined the cost function as a general estimate of the optimal cost function which exploits all the available learning (for where n is the number of training pairs, N the number of test pairs, and D the Hilbert. The QNN meets the theoretical estimation and confirms the remarkable ability of our QNNs to generalize.




In both plots, the insets show the performance of the quantum neural network under approximate depolarizing noise. the colors show the strength t of the noise: black t = 0, violet t = 0.0033, orange t = 0.0066, yellow t = 0.01. and Simulation - a confers the knowledge of the network to infer. We will be training a 3-3-3 network for 1000 rounds with n = 1, 2.

We have created 8 pairs of training data and evaluated the cost function of 10 pairs. Matching and fixed value(orange points) and required value((violet points) of the optimal cost function.

Simulation - b gives the robustness of the QNN to noisy data. We trained a 2-3-2 network with 100 training pairs. In the plot, the number on the x-axis shows us that how the number of pairs followed by a pair of noisy (i.e. random) pairs, and the cost function is evaluated for all "good" test pairs.

## VI. Conclusion

The network architecture enables a Decrease in the number of intelligible qubits required to store the central states needed to evaluate a QNN. And to store several qubits compared with the width of the network. The network to estimate the derivative of the cost function.We have examined the fundamental quantum generalizations of perceptron and neural networks and thereby advancing an efficient quantum training algorithm. The resulting Quantum Machine Learning algorithm shows remarkable abilities, including, the ability to generalize, resistance to the noisy training data, and an absence of phenomenon of exponentially fading inclinations partly significant parametrized quantum circuits in the cost function landscape. As we know most of the algorithms are extremely sensitive to noise Thus, Concluding the quantum perceptron and analyzing the effects of overfitting, and optimized implementation on the next span of NISQ devices. ( 'Noisy Intermediate-Scale Quantum' devices)

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