Quantum Annealing Assisted Deep Learning for Lung Cancer Detection

Andrew Ward[1], Nicholas Bambos, PhD[1,2], Parag Mallick, PhD[3]

[1]Department of Electrical Engineering, Stanford University; [2]Department of Management Science and Engineering, Stanford University;
[3]Department of Radiology, Canary Center at Stanford for Cancer Early Detection

Introduction

Lung cancer is the deadliest form of cancer worldwide (**20% of worldwide cancer deaths, 158,080 US deaths in 2016**), and is often misdiagnosed. Promising work has recently attempted to assist and improve lung cancer diagnosis and prognosis using deep learning and other machine learning techniques [1][2]. However, new techniques are needed to look more holistically at the input data and improve prediction accuracy.

Quantum annealing promises exponential improvements for many optimization problems. Recent studies using Restricted Boltzmann Machines (RBMs) and quantum annealing for image processing have yielded promising results[3][4], but no study has yet attempted to apply these practices to medical imaging.

Project Goal

The goal of this work is to determine the potential improvements that quantum annealing, used jointly with deep learning, can offer to lung cancer image classification and diagnosis.

Related Work

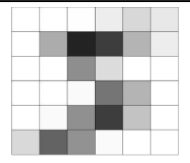
Study	Key Result
Google 2015	QA has ~100,000,000 speedup on synthetic problems
Lockheed Martin 2015	QA/CNN identifies handwritten digits 
Yu et al. 2016	Automated machine learning diagnosis/prognosis pipeline
Li et al. 2016	CNN accurate identification of lung nodules
D-Wave 2016	QA has ~1,000 speedup on practical problems
LANL 2017	Algorithm uses QA to learn facial features 

Figure 1: Key studies related to machine/deep learning applied to lung cancer [1][2], QA outperforming classical computation [5][7], or QA used in deep learning contexts [3][4].

Quantum Annealing

Background

- D-Wave 2X QPU
- 1135 Qubits
- 15 millikelvin
- Solves quadratic unconstrained binary optimization by annealing from quantum state to classical state

$$E(t) = (1 - f(t))H_Q + f(t)H_P$$

$$H_P = \sum_{i=1}^{N} a_i q_i + \sum_{<i,j>} b_{ij} q_i q_j$$

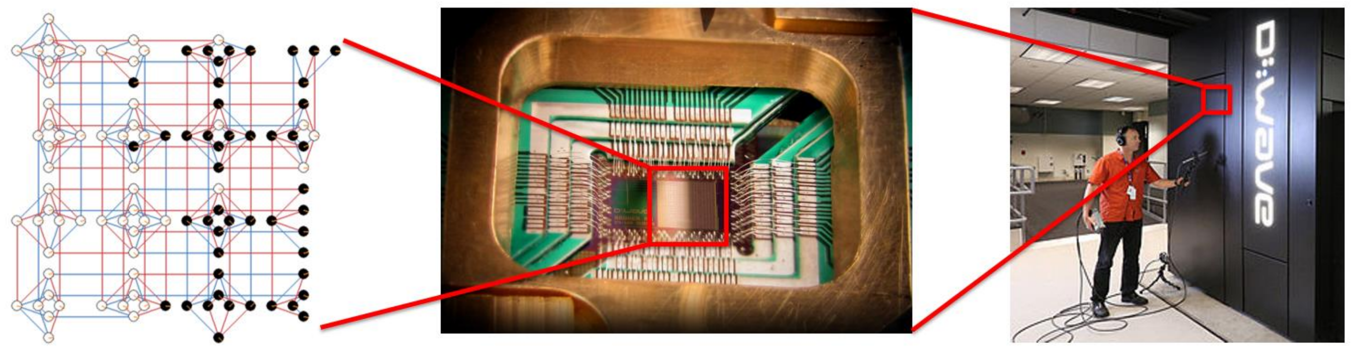


Figure 2: Left: graphical representation of qubit layout on the D-Wave chip; middle: D-Wave quantum processing unit; right, entire D-Wave machine (exterior visible).

Model and Results

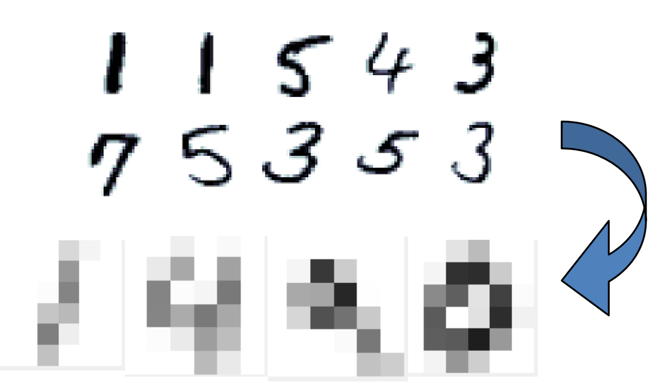
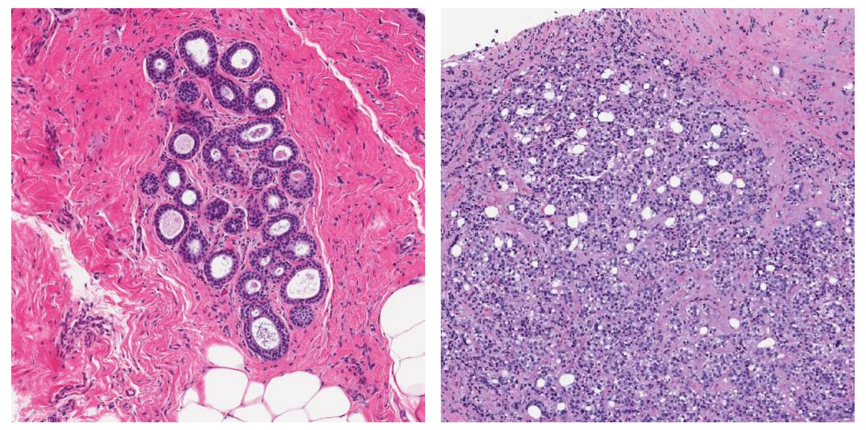


Figure 3: MNIST
- 60,000 handwritten numbers
- Standard dataset
- 28x28 grayscale
- Resized to 6x6 to fit on D-Wave machine

Figure 4: Cancer Dataset
- 144 H&E stained tissue sample slides
- Augmented by rotation, mirroring
- 500x500 color



Model Architecture

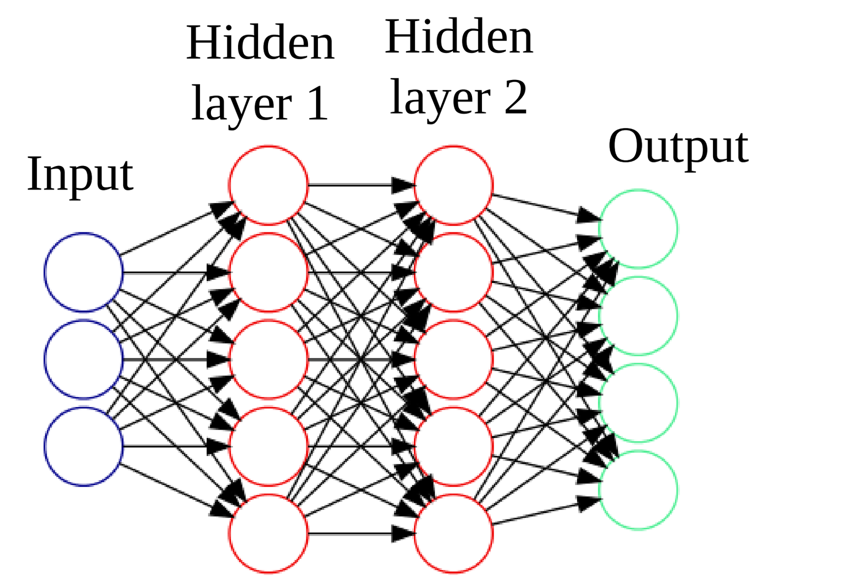


Figure 3: Deep Belief Network architecture. The input layer and hidden layers all have 36 nodes, while the output layer has 10 nodes.

True update:

$$w_{ij}^{t+1} = \alpha w_{ij}^{t} + \varepsilon\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{model}\right)$$

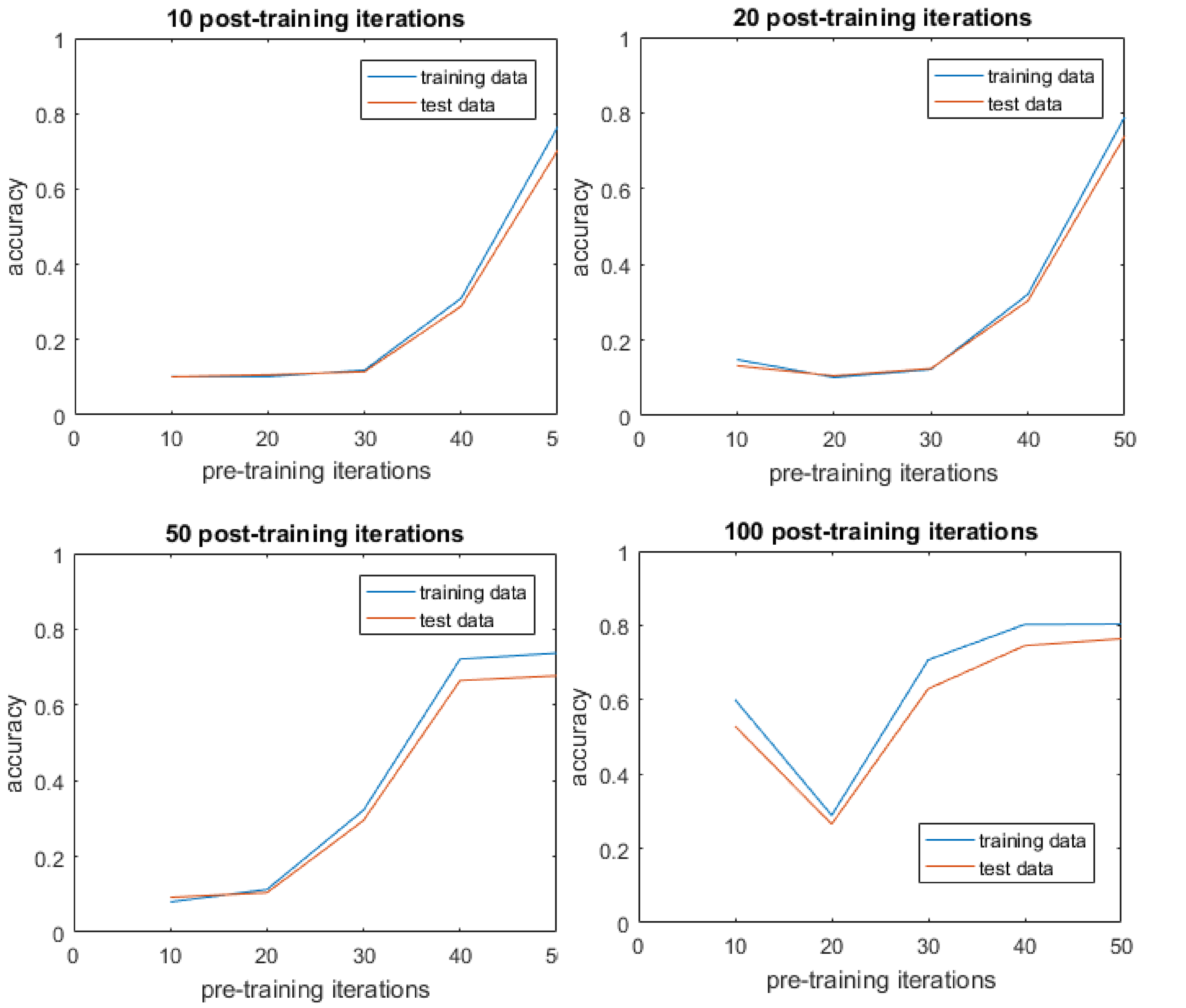
Classical update:

$$w_{ij}^{t+1} = \alpha w_{ij}^{t} + \varepsilon\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{CD-recon}\right)$$

Quantum update:

$$w_{ij}^{t+1} = \alpha w_{ij}^{t} + \varepsilon\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{Q-sample}\right)$$

Classical Training Results



Future Work

The long-term goal of this research is to engineer a hybrid deep learning/quantum annealing pipeline that will facilitate early cancer diagnosis. A schematic of this hybrid pipeline is shown in Figure 6. Quantum annealing could be used in an RBM/DBN context to extract features from images, or speed up analysis of extracted features.

In the short term, a classical feature extractor could be used to identify a small number of relevant features, which could then be analyzed directly on the D-Wave architecture and then compared to classical performance.

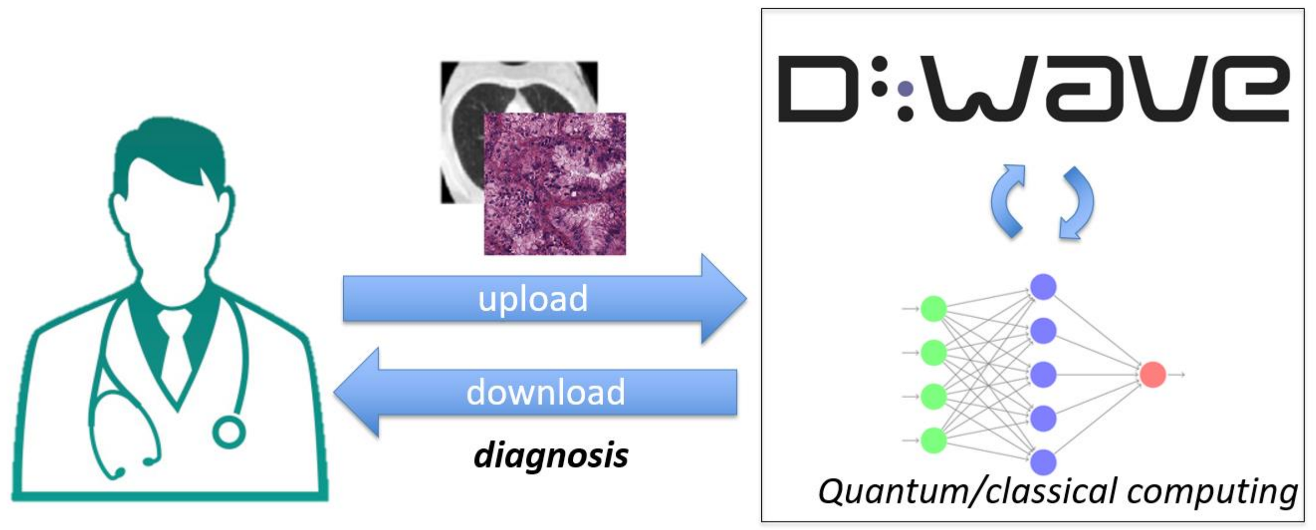


Figure 6: Proposed quantum/classical lung cancer imaging pipeline to assist doctors in diagnosis and prognosis.

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Contact Information
Andrew Ward, atward@stanford.edu