Rob Grau

svb558

May 7, 2025

Deep Learning advancements in Quantum Machine Learning

Table of Contents

1. Introduction
2. Quantum Recurrent Neural Networks for Sequential Learning
5. Nav-Q: quantum deep reinforcement learning for collision-free navigation of self-driving cars
6. Q-SupCon: Quantum-Enhanced Supervised Contrastive Learning Architecture within the Representation Learning Framework
8. Quantum Transfer Learning for Sentiment Analysis: an experiment on an Italian corpus
10. Quantum deep learning-based anomaly detection for enhanced network security
12. Deep Q-learning with hybrid quantum neural network on solving maze problems
13. Deep Ensemble learning and quantum machine learning approach for Alzheimer's disease detection
15. Quantum deep generative prior with programmable quantum circuits
16. Conclusion
16. Statement on LLM usage
16. Bibliographic References
19. Appendix A – Classification
23. Appendix B – Annotated Bibliography

Introduction

Quantum machine learning is a relatively new field of quantum computing with most major developments coming in the past 10-15 years. It can be traced back as early as 2002 when a 'quantum matching machine' was developed [11] and reached an important milestone when it was proven that quantum computing could solve a system of linear equations [8]. This rapid development can also be attributed to quantum computing's promising advantages over classical or non-quantum computing by way of several properties of quantum mechanics. Quantum superposition allows multiple states to be represented simultaneously allowing for parallel computation of problems. In comparison to a classical computer's storage of information on a bit or, for clarity, a classical bit, a quantum computer stores information in a quantum bit or qubit. Additionally, quantum entanglement allows for the qubits to interact with each other opening up a range of possibilities that are not possible in classical computing. [29]

John Preskill summarized some of the challenges facing quantum computing in a 2018 paper[4] that still hold true today. Quantum computing suffers from several drawbacks related to the quantum hardware necessary to perform operations. Notably, quantum particles need to be isolated from other particles in order to behave according to their quantum properties. However, it is necessary to interact with a quantum environment in order to process data or convey instructions. This conflict leads to quantum noise and state degradation, called decoherence, that limit the circuit depth and complexity that can be executed on a quantum computer.

Preskill also coined a term for the current hardware state, NISQ, which stands for Noisy Intermediate-Scale Quantum- Noisy means control of qubits imprecise and intermediate scale means that only 50 to a few hundred qubits can be successfully included in a program before the error rate becomes to large to receive a meaningful result. This makes functional error correction necessary to stabilize qubit storage into something that allows for a large scale. Finally, there isn't an easy way to move large amount of data from classical to quantum so encoding large amounts of date in quantum RAM has high overhead.

Even with these considerable challenges, quantum deep learning has been developed and more recently moved from early theoretical work into concrete experiments run on modern NISQ hardware. These developments have come across many domains including healthcare [20], cybersecurity [22], quantum error correction[19, 25], quantum hardware[24, 28], improved quantum circuits [27], and quantum tomography [17]. Below are several papers with interesting advancements of quantum machine learning:

Quantum Recurrent Neural Networks for Sequential Learning

In Yunan et al, [10] authors want to design a Quantum Recurrent Neural Network that's realistic for the NISQ hardware environment that exists in today's quantum world. If one were to take an approach to the quantum circuit where all QRNN circuits are run one after another, mirroring the classical RNN structure directly, then there will unfortunately will be decoherence problems on today's hardware. The key idea of the paper is a staggered quantum RNN circuit where the qubits are rotated to prevent decoherence.

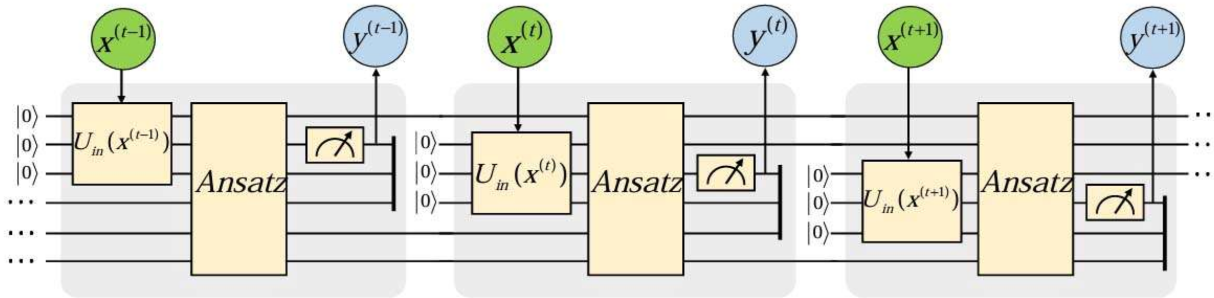
It's helpful to momentarily review what a classical RNN is. The R stands for recurrent and is used for sequential / temporal data. The classical recurrent network uses a function that takes the input from the most recent item in the time series and combines it with the output from the last step/layer to create an updated state that may be transformed based on activations. After activations, you have the new output layer. The most recent layer's output in the classical RNN implicitly contains output from all of the previous layers because of recursion in the RNN structure.

In regards to challenges with design of a quantum circuit, a common bottleneck for hybrid classical-quantum algorithms is the encoding of classical data into quantum qubits. Amplitude encoding is a commonly used method to encode exponential classical bits into quantum superpositions, the downside is that quantum circuits grow exponentially with more datapoints. Alternately, angle encoding of classical data takes the datapoints and represents them as angle rotations around the computational basis. With angle encoding, qubits can just be equal to the number classical datapoints. This is more efficient and because more qubits lead to more errors in an NISQ environment, efficiency is a requirement. Thus the authors chose to use angle encoding on the data. The authors took error rates into consideration, and actually used three qubits for a single classical bit. This is because of unreliable error correction to which the alternative is redundancy.

An ansatz design is used to perform the work of the quantum RNN. The functionality of an ansatz circuit is provided by a parameterized quantum circuit that has adjustable quantum gates. A quantum gate is a unitary operation transformation performed on a qubit. Because the gates are adjustable, the values of the gates in the ansatz are what is trained by the model.

For measurement, the process must be rerun multiple times. This is because a quantum state is represented by probabilities of the state belonging to a basis state. When quantum measurement occurs, the result is only one basis state. Only after multiple runs will an estimate of the probabilistic expectation be available.

Paper then discusses what a quantum QRNN would look like in a closed system or theoretical system where noise and decoherence were not factors. In this setup, you could model the qRNN directly after a classical RNN setup. In this design, a quantum register which is a set of qubits, takes a new input datapoint and a second register that holds the ongoing value of the variables. The ansatz is applied across all of the quantum bits and a measurement of one of the state qubits is made to create an output value. While quantum register with new data is reset prior to each input, the other register is not reset and holds its value throughout the process. In open systems or real world scenarios with NISQ hardware, it is not realistic to expect the state qubits to hold onto their state value for many iterations.



This leads us to the proposed staggered qRNN model, where after each iteration of the RNN process, the qubit register holding the system state shift by one qubit. For example, if there are six qubits, three for the state register and three for the new input register, then only two of the three qubits holding the state will remain for the next iteration, paired with one of the qubits that was previously used for new data. The remaining three qubits will be reset and used for new data. In this scenario, after three iterations the state qubits will have completely shifted to the qubits that were previously used for input data. In fact, the state will only have to be maintained for n+1 iterations where n is the number of qubits in the quantum register. This is the key advantage of the staggered qRNN over the plain qRNN.

There is another challenge to implementing classical machine learning methods on quantum computers and this comes in the form of optimizing a loss function. Unlike classical machine learning, backpropagation cannot be computed because that relies on saving the state of the environment, an impossibility in quantum computing

An approximate derivative can still be calculated on the quantum computer, it requires running the quantum circuit twice with slightly different values and using the difference for computing loss functions.

Researchers examined the performance of two QRNN systems (called plain and staggered) are then compared to a classical RNN that is configured similarly to the QRNN setup.

In the experiment, a circuit iteratively took seven days of input data which was then used to generate a prediction. The two quantum RNN models performed similarly to the classical RNN on actual data and were even more accurate for a few features such as wind speed in meteorological data. The study also varied the size of the qubit registers of qubits. Prediction accuracy increased as quantum registers grew from 4 to 6 to 8 qubits.

The experiments showed that a staggered quantum RNN model could be both accurate and possible to implement on modern hardware.

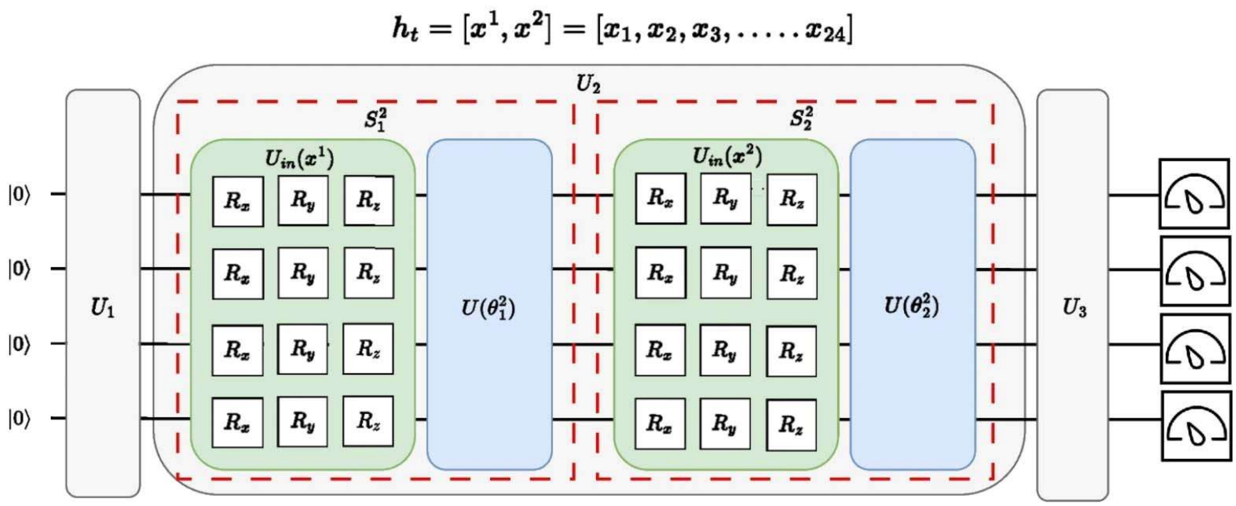
Nav-Q: quantum deep reinforcement learning for collision-free navigation of self-driving cars

A recent paper by Sinha, et al [7] discusses quantum reinforcement algorithms used in the self driving car domain. The authors note that they are not the first to consider quantum reinforcement learning however the earlier work have been simulated in simplified environments while demonstrating collision avoidance on self driving cars is more realistic test for quantum reinforcement learning.

Central to any work involving self driving cars is real-time optimization of on-board camera data. The classical approach to utilize partially observable Markov decision processes and Deep Reinforcement Learning. The proposed model is a hybrid quantum classical model where the key idea is to have a quantum computer do the work of the reinforcement learning agent. In particular, the authors use an actor-critic model for the agent. One particular appeal of this model is that the quantum circuit is only used in the critic because that algorithm is only needed for training. This is important because any part of the system that is used in testing will have to be part of the car design. Today's quantum computers are still housed in large datacenters with carefully controlled environments. No vehicle comes close to being a feasible host for a quantum computer.

In the current classical training for self-driving cars, NavA2C is the baseline on which the authors built their quantum design. NavA2C combines the car's path planner with a modified reinforcement agent. The deep reinforcement learning agent has four main components: an encoder, an actor, a critic and an LSTM cell. The NavA2C agent is responsible for calculating the speed action for the car. The Nav-q critic uses a parameterized quantum circuit that takes an input of the hidden state from the LSTM cell.

A parameterized quantum circuit is a common approach seen in quantum machine learning designs. At a general level, the system state is encoded onto the qubits of the quantum circuit and then it is run through what's known as an ansatz which is a rotational gate where the angle can be set programmatically. The output of the circuit can then be taken and classified.



In the initial design of the Nav-q quantum circuit, 24 classical parameters from the LSTM cell are encoded onto 4 qubits across two layers. The output is taken from the quantum circuit and linearly recombined as a fully connected layer that feeds back into the LSTM cell. The authors noted the quantum process was actually quite slow for this design and they subsequently reduced the design to 2 qubits with 1 layer that only took 6 parameters from the LSTM cell hidden state.

After model refinement, training occurred and the designs were tested in standard CARLA driving model simulators. The quantum model performed well in optimal route model while the classical model outperformed the quantum model in terms of collision avoidance. Aside from simulator performance, the authors investigated the percentage of active parameters relative to the total number of parameters in the model, called the normalized effective dimension. The number was 10 times higher for the quantum model than the classical model, suggesting that the quantum model has a better ability to model more complex functions.

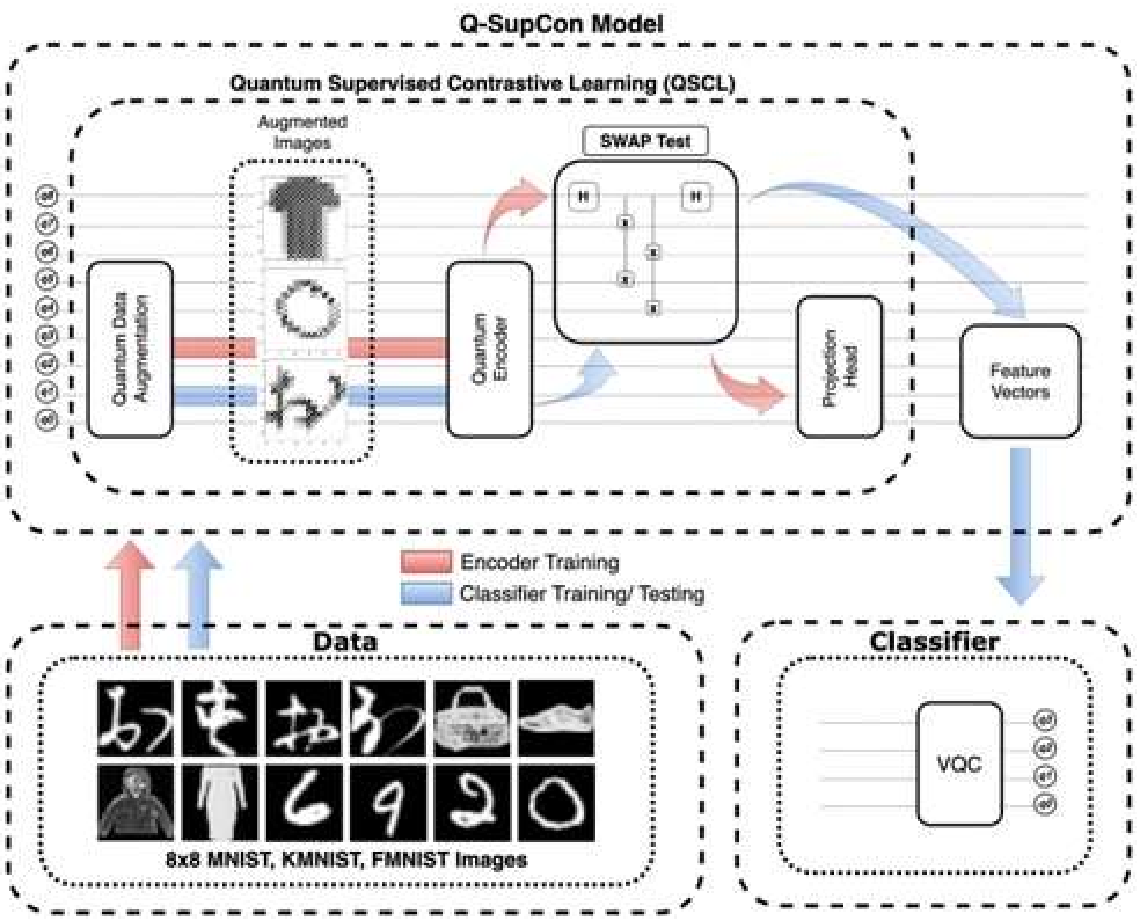
The quantum system still has drawbacks. Although the authors ran the Nav-Q model through a more complex driving simulation than previous works, it was still simulated in a noiseless quantum environment, which unfortunately is not how modern quantum hardware operates. When noise was introduced into the Nav-Q simulations, the stability of the learning rate decreased significantly and the time required to train the model increased.

Q-SupCon: Quantum-Enhanced Supervised Contrastive Learning Architecture within the Representation Learning Framework

Don et al. [6] addess dataset sparsity with a method called Q-SupCon, which is short for quantum contrastive learning. Contrastive learning is a method of comparing pairs of similar and dissimilar samples in order to learn from both the maximum and minimum values of similarity.

Deep learning networks have a need for large datasets to complete proper training, however, some domains such as healthcare have privacy restrictions which create barriers to collecting a large dataset. This presents the setup for the ‘curse of dimensionality' where a spare dataset lacks enough datapoints to be accurately represented with a lower dimension model, however higher dimension models require more data to fight overfitting.

When quantum computing can encode complex representations of data into a smaller space, the data behaves differently. This is why it investigated for use in contrastive learning as it could potentially simplify the process or combat overfitting. Researchers created a model with four separate quantum functions—data augmentation, encoder, projection head, and classifier.



The quantum data augmentation was developed as part of a previous work by Chalumuri, et al [30]. In this application, small parts of the image were sampled and encoded in the quantum circuit. Rotation gates are applied and a further not gate will flip bits to introduce noise. The noise is applied the original image to create more data samples.

The quantum autoencoding function employes a parameterized quantum circuit to compress the images into fewer qubits. Some of the bits are transformed into the feature vector that will be classified. Parameterized quantum circuits include angle rotation gates where the angle of the gate is trainable.

The third quantum feature is the projection head. It acts as a fully connected layer after the autoencoder. Notably, it is only utilized for training the autoencoder's parameters and is not needed for the classifier.

The final component of the algorithm is a variational quantum classifier method is used on the feature vectors to determine classification. In training the VQC was optimized with a gradient method and researchers had to deal with gradient dropout that is sometimes called a barren plateau. An initial guess was used with cross entropy to deal with dropout.

The authors created a model that perform fully quantum supervised learning on actual quantum hardware, specifically using trapped ion infrastructure. This is impressive given the aforementioned state of NISQ hardware. Even so, some compromises had to be made on the evaluation datasets to make it possible to run. The MNIST, FMNIST, KMNIST datasets were used, however, image size was reduced to 8 x 8 pixels. The full datasets were not used either. The training datasets were reduced to 25-150 images per class and classes were randomly sampled multiple times. Images used for training in were not reused with a different random sample of classes.

After testing on similarly limited datasets of 25 images, test accuracy for Q-SupCon on the MNIST and FMNIST was 80% while KMNIST had a 60% accuracy. The classical ResNet baseline had a 20% accuracy on MNIST and FMNIST and a 40% accuracy on KMNIST. At 150 test samples, accuracy for both quantum and classical models was more than 90%.

These results are very promising given that barriers to data collection will likely remain in place. Quantum remains an expensive method for computation, however, this shows how it can be a benefit in spares data scenarios.

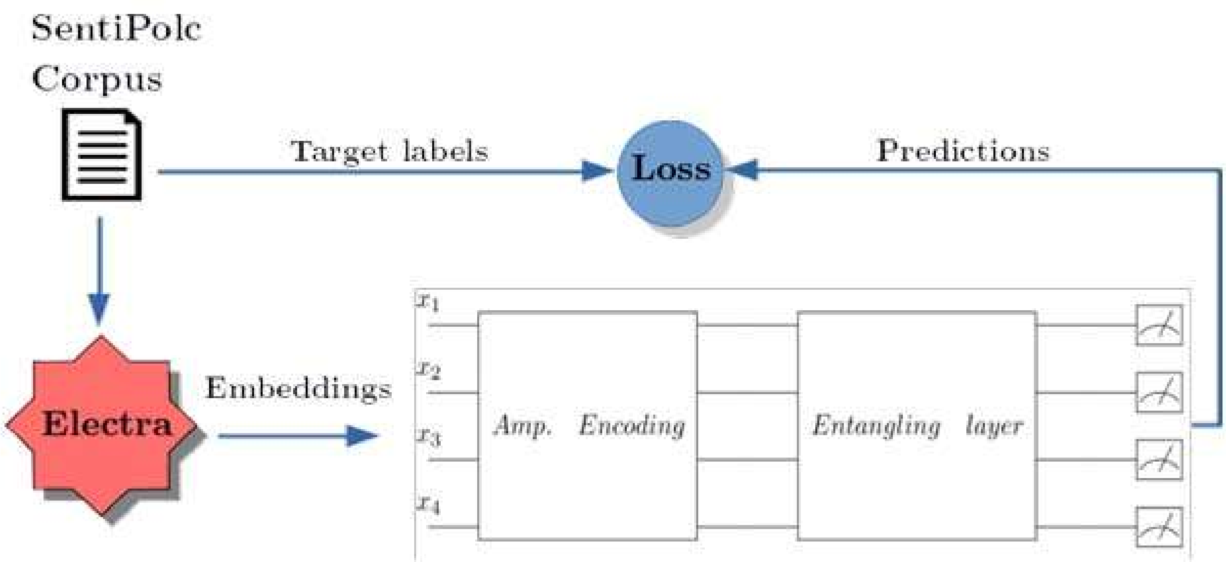
Quantum Transfer Learning for Sentiment Analysis: an experiment on an Italian corpus

In a paper by Buonaiuto et al. [5] , quantum computing is investigated to see if it offers any advantages to natural language processing (NLP). NLP is resource intensive and the hope is that quantum computing may be able to alleviate some of the resource pressures.

Within the field of quantum computing the task of sentiment analysis was selected for study. Sentiment analysis is a standard NLP task where the primary emotional tone in a text is identified. Additionally, if quantum computing can be used to combine the sentient analysis with document retrieval makes the retrieval process more intelligent and powerful.

This research looks at quantum embedding where quantum concepts of superposition and entanglement are used to capture semantic relationships between words.

Quantum approach is unsupervised machine learning using a density matrix generated from two sentiment dictionaries. This work features a Variational Quantum Classifier (VQC) that is used with a language model to make classifications of sentiment. The variational quantum classifier is an ansatz with a single rotational gate followed by CNOT gates. During training, an optimizer finds the quantum parameters that best capture the target labels. This is a relatively straightforward implementation of a VQC.



The workflow is as follows: Text is fed into a classical NLP model called Electra. Electra is used to extract work vectors. The vectors are then encoded in to a quantum circuit and sent to the VQC. After passing through the VQC, word relations identified in quantum circuit are then used as inputs to a classical LSTM. High dimension word vectors are encoded into a probablistic space with a generative tensor network to classify text.

The current NISQ hardware limits quantum NLP to relatively easy tasks or small datasets. In the case of this experiment, the training and test datasets were reduced to 4476 sentences for training and 500 sentences for test. On the other hand, the dataset had 768 features and they were all encoded into 10 qubits. That is possible because quantum superposition allows an exponential number of classical data points to be represented. The log (base 2) of 768 falls between 9 and 10, so the 768 features were represented with just 10 qubits. The extra information for the unneeded features 769 through 1024 were filled in with zeros. Finally, although this experiment used a simulator for the quantum circuit, the number of qubits and the design of the VQC are sufficiently compact that it would have been feasible to run this on modern quantum hardware.

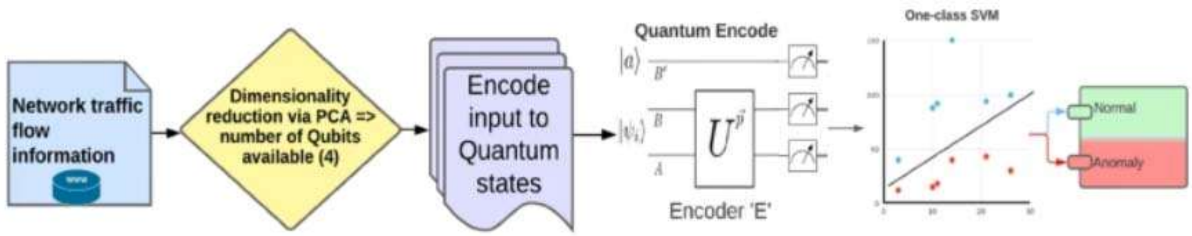
The results of the experiment were measured using an F1 score. The hybrid quantum circuit achieved an F1 score of 0.77 while the classical baseline achieved an F1 score of 0.75. Some other notes, the classical baseline algorithm used preprocessing of the language data to get a higher F1 score where as the quantum algorithm did not do any pretraining. The author's classical baseline was not exactly the same as quantum model, so it's hard to extrapolate too much. It does show that there are positives in the quantum model that may indeed come from the quantum properties.

Quantum deep learning-based anomaly detection for enhanced network security

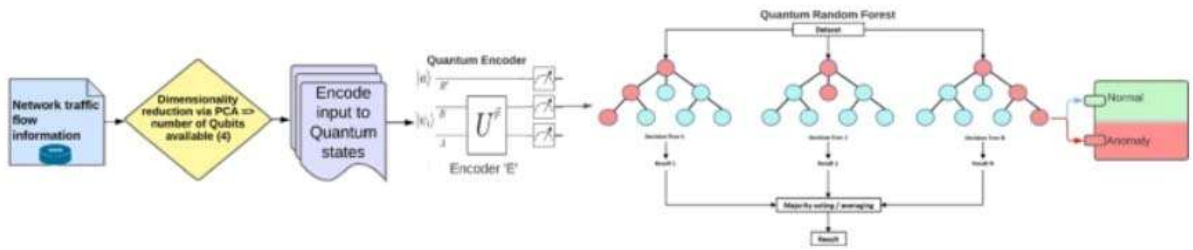
In Hdaib et al, [2] three different quantum approaches to machine learning are compared to see what is most effective at detecting web traffic anomalies. Additionally, a quantum encoder is employed to compress the classical data to a format that can be processed by the quantum algorithms. The three proposed algorithms are Random Forest, kNN, and a one layer SVM. The quantum parts of the algorithms are not completely new as they were originally proven in 2014 [12, 13, 31] however this application is interesting in analyzing the three different models with each other on actual non-theoretical hardware.

Web security involves monitoring traffic, finding anomalies and mitigating them. Quantum machine learning has not commonly been used for this application. The authors want to find out if quantum's ability to process correlated features through entanglement will improve on classical approaches to web security. The previous work in quantum anomaly detection used supervised learning. The proposed algorithms are forms of unsupervised learning.

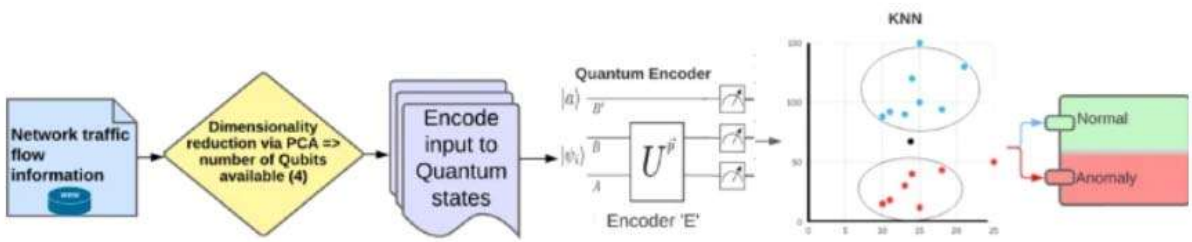
The quantum encoder in this application is not simply converting classical information into quantum. It has a parameterized quantum circuit that compresses the state but also can be trained on the parameters similar to the principal component analysis machine learning method where data is projected onto lower dimension vectors. After the state is compressed, fresh qubits are introduced to reconstruct the state. The encoder can be used on its own to detect anomalies based on how much error was in the reconstruction of the quantum state.



(a) Framework 1: Union of QAE and one-class SVM.



(b) Framework 2: Union of QAE and quantum random forest.



Subsequent to the encoder circuit, three different machine learning approaches are used by way of different quantum circuit design. The random forest has another parameterized quantum circuit, however this ansatz is more complicated than just a single rotation gate like many other PQC are. It uses multiple gates to map the feature map of the input onto the quantum qubits. For quantum kNN, the quantum circuit uses a swap test to measure proximity of the datapoints. For three dimensional proximity such as the measurements for quantum particles the angle between the two distance vectors is measured by taking the inner product of the two vectors. A quantum swap test followed by a measurement performs this function. The one layer SVM design uses single z-axis rotation gates followed by 2 qubit z-axis rotation gates. Finally, a binary classification is performed on the data (with all of the different algorithms) where the outcome is either an anomaly in web traffic or not.

For the experiments, the web anomaly datasets KDD99, IOT-23, and CIC IOT 23 were tested. Prior to the work, data preprocessing was performed. Of note, there is a class imbalance challenge with web anomaly detection, so undersampling was used to reduce the majority class without eliminating anything from the minority class. Normalization, one hot encoding and PCA reduction was also used. The experiments were run on IBM superconductor quantum hardware, however, the parameter optimization was first computed with a qiskit simulator and pytorch. For completeness, the models were compared against a classical baseline.

Because of the class imbalance issue, accuracy scores were not very revealing, so F1 scores were used instead of evaluation. The quantum kNN framework achieved the highest F1 score of any model at 98.26% on the CIC IOT 23 data. The quantum SVM performed well on the network flow data in the KDD99 dataset where its 97.19% F1 score was the best of any other model on the KDD99 data. The quantum models all outperformed their classical counterparts.

Despite the encouraging results, the authors note that the quantum experiments were limited by the amount of preprocessing and quantum circuit modification that had to be performed to feed the real world data into the quantum circuits. Additionally, the authors shared information on the autoencoder training relative to the number of qubits. At 4 total qubits with 2 latent qubits, training time was 1.64 hours with a fidelity of 99.6%. With a small increase to 6 qubits and 4 latent qubits, training time jumped to 7.85 hours with a drop in fidelity to 86.1%. The scaling problem is immediately evident.

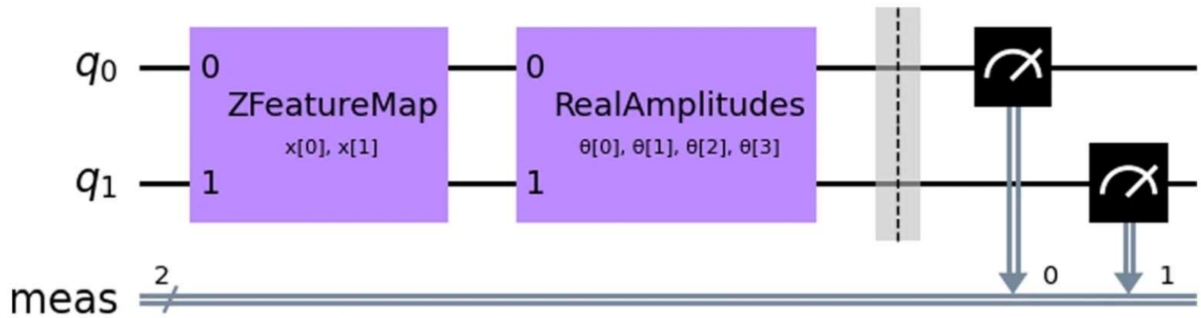
Deep Q-learning with hybrid quantum neural network on solving maze problems

In Deep-Q learning with hybrid neural networks by Chen, et al [1] use quantum deep learning to solve maze problems. These problems are solved with reinforcement learning using a reward signal, specifically the Markov decision making process (MDP). Solving a maze problem classically can be computationally expensive and the hope is that quantum computing will reduce the overall complexity of the task.

In MDP, an agent observes the state and then selects an action and receives a reward based on the desirability of the action. The process repeats at the next state and the agent is expected to optimize reward. One option researchers have is to create a quantum walk algorithm and a variational quantum circuit (VQC) to encode classical agents with state information. The second option is to use a fully quantum model. The fully quantum model is promising but hampered by state of NISQ hardware.

The author’s eventual quantum approach is a hybrid one that uses a 'model free' method of estimating state-action pairs and then using that estimate to update the value with a parameterized (VQC). The model free method is referred to as Q-learning as the model estimates a Q-value or cumulative reward.

In the proposed hybrid model, a classical agent updates a quantum learning table by estimating quantum states and storing them. The agent selects the highest Q-score value available to it and gets a reward value from the environment. Those are sent to the DNN. To prevent correlation between samples, the agent may also select a random past experience. This is an effort to prevent overfitting. On the DNN side, the neural network takes the input and outputs a range of actions and Q-score.



In terms of quantum structure, a variational quantum circuit is used as the last layer of the DNN. The quantum circuit design uses two qubits which are manipulated by feature encoding and ansatz module to return the result. The feature encoding with z-axis gates and the ansatz alternates between y-axis rotation gates and cnot gates for entanglement.

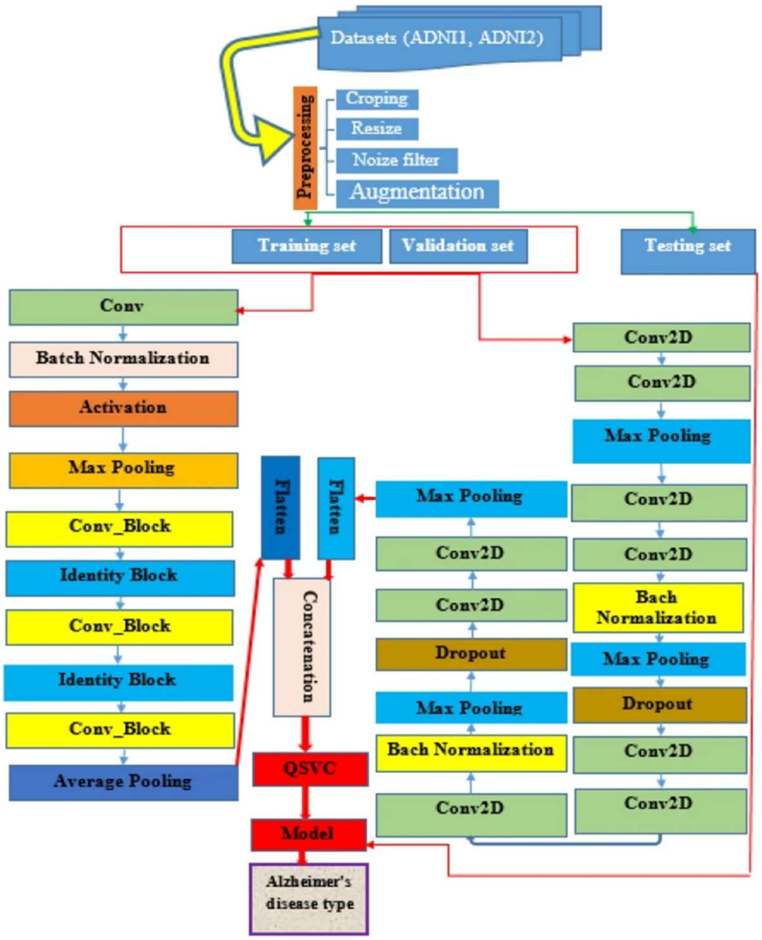
For the experiment, the algorithm had to search 4x4 and 5x5 mazes. As is typical with maze problems, a path had to be created that went from the entry cell to the exit cell without touching any walls. A classical CNN was also run in the same environment as a baseline.

The experiment results favored the classical CNN. The classical CNN had a better win rate in 4x4 maze (89.94% vs 85.19%) and a much shorter training time (only 1/8th of qNN training). The quantum CNN improved its win rate on 5x5 maze (93.13%) but still was inferior to traditional CNN which had a 94.87% win rate and faster training time.

The researchers did not utilize NVIDIA's cuQuantum platform but are hopeful that future work with it may yield training advancements for their structure. In the meantime, the quantum environment remains feasible but strictly worse than classical.

Deep Ensemble learning and quantum machine learning approach for Alzheimer's disease detection

A novel application of quantum deep learning was presented by Belay et al [3]. in which an ensemble approach is applied to quantum machine learning. The research utilized a set of publicly available ADNI dataset of MRI scans for Alzheimer's disease patients. In this task, deep learning checks for disease markers in the brain scans and classifies the images.



Two classical deep learning models (VGG16 and ResNet50) are run separately and instead of a final classification layer, the output from each is flattened, concatenated, and fed into a quantum SVM classifier. There are a number of deep neural networks that have been created to solve this problem in related work section. A 2023 model reportedly achieved 99.68% accuracy, which is considered state of the art.

The model was run a number of times with different input models. The VGG16 and ResNet50 models were run separately and as an ensemble without the SVM classifier. They were also run with both a classical and quantum SVM classifier. The parts of the models before SVM were all run in the same configuration. VGGNet has nine convolutions, two batch normalizations, three max-pooling, two dropouts, and one flattened layer. ResNet 50 model has one convolution, one max-pooling, one average polling, one batch normalization, one activation, two identity blocks, three conv blocks, and one flattened layer.

Results for the classical algorithms without any SVM were unremarkable, with VGGNet having a 90.11% accuracy rate and the ensemble 90.58%. ResNet50 alone scored only 75.04%. With the classical SVM the accuracy results were 85.24% for VGGNet, 82.24% for ResNet50, and 86.78% for the ensemble model which was actually a step backwards. The authors did note that the classical SVM scores were lower because they used pretrained models that were not trained on the ANSI MRI images. With the quantum SVM the results were much better with 95.65% accuracy for VGGNet, 91.56% accuracy for ResNet50, and 99.89% accuracy for the ensemble model.

It should be noted that to fight class imbalance, data augmentation was performed and the quantum models were all simulated so they did not actually achieve this result in a modern

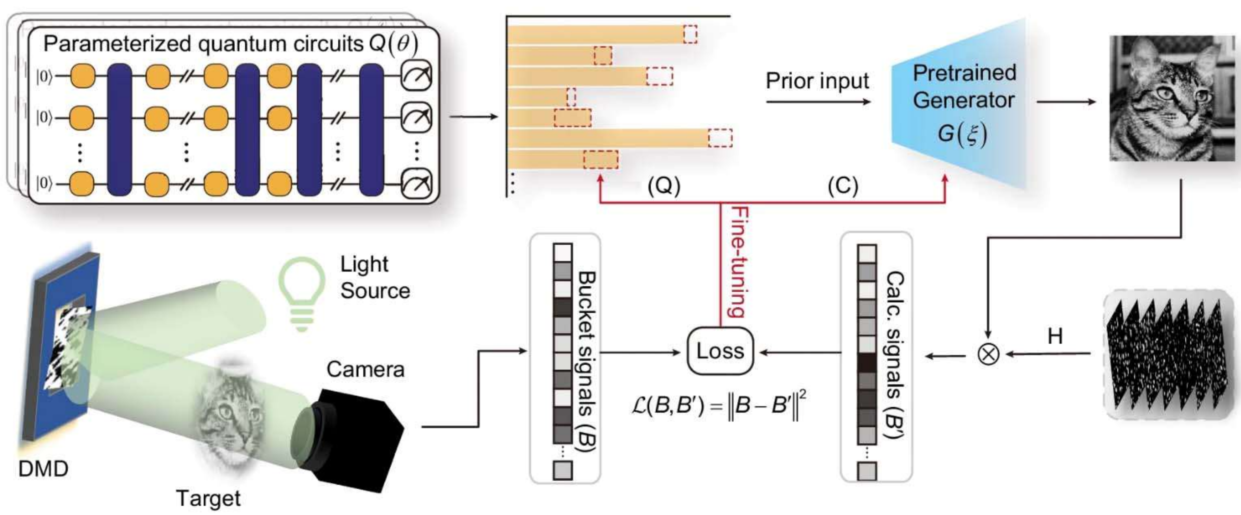
NISQ hardware environment. Even with that, it remains an encouraging result for the use of quantum ensemble models.

Quantum deep generative prior with programmable quantum circuits

In Quantum deep generative prior with programmable quantum circuits by Xiao et al, [9] the authors discuss the role of quantum computers in generative tasks. They investigate what is possible to accomplish in the near future with NISQ hardware. One common approach in quantum machine learning is to utilize a parameterized quantum circuit (PQC). It's difficult to scale the depth and width of PQC circuits with hardware limitations.

The authors decide to test classical image generation via GAN assisted by a PQC. The authors design a range of computer vision tasks to be completed such as ghost imaging where a low resolution image is created and the quantum algorithm must reconstruct it.

For this process, classically CNNs capture image statistics during processing that can be treated as a prior image. Higher dimension images can be approximated by a learnable generator (the GAN) that captures a latent space. The idea is that a quantum deep generative prior (QDGP) using PQC to generate a latent space will be able to capture a larger dimension thanks to quantum capabilities.



For the experiment, Images were created by taking an original image and transforming it into a degraded version. These ghost Imaging priors can be created using extremely low light with as little as a few photons. Research with a classical solution to this problem is ongoing, however, larger datasets are often needed for training in this situation. As with many applications in data science, it is not always possible to have a robust dataset such as that. The sparse training data was simulated in the tests.

Additionally, both classical and quantum models were tested with both pretrained GANs and random initialization. A classical non-GAN model using a simple loss function was used as a baseline. Models were scores on peak signal to noise ratio and structural similarity metrics. As one would expect, both quantum and classical models performed better with more training samples. Initially, the random GANs (both quantum and classical) scored higher but as the sample space increased, the pretrained models overtook the random models in the metric scoring. The authors believe this is because the pretrained models need more data to fine tune their existing parameters. Both classical and quantum models are competitive with each other but at the highest sample rates, the quantum models perform the best. Finally, the non-GAN classical model performed the worst and was not competitive with any model which demonstrated the utility of the GAN.

In addition to the ghost imaging test discussed above, tests were conducted with category transfer, colorization, inpainting, and super-resolution. Quantum performed better than classical models in colorization and inpainting while being competitive in the other tasks.

The authors attribute the better performance of the quantum models in these tasks to the higher dimensionality created by quantum encoding of data.

Conclusion

The recent papers show that what was simply theoretical ten to fifteen years ago is now possible to create and test on quantum hardware. The hardware environment of today's quantum systems are still limiting to the overall field as experiments were all scaled down to function within current systems operating requirements. For true advancement, quantum error correction will need to improve circuits enough that they can run quantum RAM (qRAM) that several papers reference.

Statement on LLM usage

LLMs were not used in the development of this research paper. All mistakes made are my own.

Bibliographic References:

1. Chen, HY., Chang, YJ., Liao, SW. *et al.* Deep Q-learning with hybrid quantum neural network on solving maze problems. *Quantum Mach. Intell.* **6**, 2 (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s42484-023-00137-w
2. Hdaib, M., Rajasegarar, S. & Pan, L. Quantum deep learning-based anomaly detection for enhanced network security. *Quantum Mach. Intell.* **6**, 26 (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s42484-024-00163-2

3. Jenber Belay, A., Walle, Y.M. & Haile, M.B. Deep Ensemble learning and quantum machine learning approach for Alzheimer's disease detection. *Sci Rep* **14**, 14196 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s41598-024-61452-1
4. Preskill, John, Quantum Computing in the NISQ era and beyond detection. Quantum 2, 79 (2018). https://quantum-journal.org/papers/q-2018-08-06-79/
5. Giuseppe Buonaiuto, Raffaele Guarasci, and Massimo Esposito. 2024. Quantum Transfer Learning for Sentiment Analysis: an experiment on an Italian corpus. In Proceedings of the 2024 Workshop on Quantum Search and Information Retrieval (QUASAR '24). Association for Computing Machinery, New York, NY, USA, 25–30. https://doi-org.libweb.lib.utsa.edu/10.1145/3660318.3660325
6. Asitha Kottahachchi Kankanamge Don and Ibrahim Khalil. 2025. Q-SupCon: Quantum-Enhanced Supervised Contrastive Learning Architecture within the Representation Learning Framework. ACM Transactions on Quantum Computing 6, 1, Article 6 (March 2025), 24 pages. https://doi-org.libweb.lib.utsa.edu/10.1145/3660647
7. Sinha, A., Macaluso, A. & Klusch, M. Nav-Q: quantum deep reinforcement learning for collision-free navigation of self-driving cars. *Quantum Mach. Intell.* **7**, 19 (2025). https://doi-org.libweb.lib.utsa.edu/10.1007/s42484-024-00226-4
8. Aram W. Harrow, Avinatan Hassidim, and Seth Lloyd, Quantum Algorithm for Linear Systems of Equations. Phys. Rev. Lett. 103, 150502 – Published 7 October, 2009. https://doi-org.libweb.lib.utsa.edu/10.1103/PhysRevLett.103.150502
9. Xiao, T., Zhai, X., Huang, J. *et al.* Quantum deep generative prior with programmable quantum circuits. *Commun Phys* **7**, 276 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s42005-024-01765-9
10. Yanan Li, Zhimin Wang, Rongbing Han, Shangshang Shi, Jiaxin Li, Ruimin Shang, Haiyong Zheng, Guoqiang Zhong, Yongjian Gu, Quantum recurrent neural networks for sequential learning, Neural Networks, Volume 166, Pages 148-161, (2023) https://doi.org/10.1016/j.neunet.2023.07.003
11. Masahide Sasaki and Alberto Carlini, Quantum learning and universal quantum matching machine, Phys. Rev. A 66, 022303 – Published 6 August, 2002. https://doi-org.libweb.lib.utsa.edu/10.1103/PhysRevA.66.022303
12. Lloyd, S., Mohseni, M. & Rebentrost, P. Quantum principal component analysis. *Nature Phys* **10**, 631–633 (2014). https://doi.org/10.1038/nphys3029
13. Patrick Rebentrost, Masoud Mohseni, and Seth Lloyd, Quantum Support Vector Machine for Big Data Classification, Phys. Rev. Lett. 113, 130503 – Published 25 September, 2014. https://doi-org.libweb.lib.utsa.edu/10.1103/PhysRevLett.113.130503

14. Iris Cong, Soonwon Choi, Mikhail D. Lukin, Quantum Convolutional Neural Networks, Nature Physics (2019). https://doi.org/10.1038/s41567-019-0648-8
15. Jonathan Allcock, Chang-Yu Hsieh, Iordanis Kerenidis, and Shengyu Zhang. 2020. Quantum Algorithms for Feedforward Neural Networks. ACM Transactions on Quantum Computing 1, 1, Article 6 (December 2020), 24 pages. https://doi.org/10.1145/3411466
16. Marcello Benedetti, Erika Lloyd, Stefan Sack and Mattia Fiorentini, Parameterized quantum circuits as machine learning models, Quantum Science and Technology, Volume 4, Number 4, Published 13 November 2019. https://doi.org/10.1088/2058-9565/ab4eb5
17. Jerbi, S., Gyurik, C., Marshall, S.C. *et al.* Shadows of quantum machine learning. *Nat Commun* **15**, 5676 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s41467-024-49877-8
18. Sha, M., Rahamathulla, M. Quantum deep learning in Parkinson's disease prediction using hybrid quantum–classical convolution neural network. *Quantum Inf Process* **23**, 383 (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s11128-024-04588-3
19. Hu, F., Khan, S.A., Bronn, N.T. *et al.* Overcoming the coherence time barrier in quantum machine learning on temporal data. *Nat Commun* **15**, 7491 (2024). https://doi.org/10.1038/s41467-024-51162-7
20. Alona Sakhnenko, Julian Sikora, and Jeanette Lorenz. 2024. Buildung Continuous Quantum-Classical Bayesian Neural Networks for a Classical Clinical Dataset. In Proceedings of Recent Advances in Quantum Computing and Technology (ReAQCT '24). Association for Computing Machinery, New York, NY, USA, 62–72. https://doi-org.libweb.lib.utsa.edu/10.1145/3665870.3665872
21. Archisman Ghosh and Swaroop Ghosh. 2024. The Quantum Imitation Game: Reverse Engineering of Quantum Machine Learning Models. In Proceedings of the 2024 Workshop on Attacks and Solutions in Hardware Security (ASHES '24). Association for Computing Machinery, New York, NY, USA, 48–57. https://doi-org.libweb.lib.utsa.edu/10.1145/3689939.3695783
22. Rosa-Remedios, C., Caballero-Gil, P. Optimizing quantum machine learning for proactive cybersecurity. *Optim Eng* (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s11081-024-09934-z
23. Zoufal, C., Lucchi, A. & Woerner, S. Quantum Generative Adversarial Networks for learning and loading random distributions. *npj Quantum Inf* **5**, 103 (2019). https://doi.org/10.1038/s41534-019-0223-2

24. Hoch, F., Caruccio, E., Rodari, G. *et al.* Quantum machine learning with Adaptive Boson Sampling via post-selection. *Nat Commun* **16**, 902 (2025). https://doi-org.libweb.lib.utsa.edu/10.1038/s41467-025-55877-z
25. Shinde, U.U., Bandaru, R. Re-locative guided search optimized self-sparse attention enabled deep learning decoder for quantum error correction. *Sci Rep* **15**, 3615 (2025). https://doi.org/10.1038/s41598-025-87782-2
26. Liu, Y. Superconducting quantum computing optimization based on multi-objective deep reinforcement learning. *Sci Rep* **15**, 3828 (2025). https://doi.org/10.1038/s41598-024-73456-y
27. Huang, Y., Che, L., Wei, C. *et al.* Direct entanglement detection of quantum systems using machine learning. *npj Quantum Inf* **11**, 29 (2025). https://doi.org/10.1038/s41534-025-00970-w
28. Choi, S., Salamin, Y., Roques-Carmes, C. *et al.* Photonic probabilistic machine learning using quantum vacuum noise. *Nat Commun* **15**, 7760 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s41467-024-51509-0
29. E. W. Bethel et al., "Quantum Computing and Visualization: A Disruptive Technological Change Ahead" in IEEE Computer Graphics and Applications, vol. 43, no. 06, pp. 101-111, Nov.-Dec. 2023, doi: 10.1109/MCG.2023.3316932.
30. A. Chalumuri, R. Kune, S. Kannan and B. S. Manoj, "Quantum–Classical Image Processing for Scene Classification," in *IEEE Sensors Letters*, vol. 6, no. 6, pp. 1-4, June 2022, Art no. 7002004, doi: 10.1109/LSENS.2022.3173253.
31. Lu, S., Braunstein, S.L. Quantum decision tree classifier. Quantum Inf Process 13, 757–770 (2014). https://doi.org/10.1007/s11128-013-0687-5

Appendix A – Classification of Papers

The papers are broken down into primary, secondary, and foundational sources. The reference numbers from the bibliography above are preserved.

Primary Sources

1. Chen, HY., Chang, YJ., Liao, SW. *et al.* Deep Q-learning with hybrid quantum neural network on solving maze problems. *Quantum Mach. Intell.* **6**, 2 (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s42484-023-00137-w
2. Hdaib, M., Rajasegarar, S. & Pan, L. Quantum deep learning-based anomaly detection for enhanced network security. *Quantum Mach. Intell.* **6**, 26 (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s42484-024-00163-2

3. Jenber Belay, A., Walle, Y.M. & Haile, M.B. Deep Ensemble learning and quantum machine learning approach for Alzheimer's disease detection. *Sci Rep* **14**, 14196 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s41598-024-61452-1
5. Giuseppe Buonaiuto, Raffaele Guarasci, and Massimo Esposito. 2024. Quantum Transfer Learning for Sentiment Analysis: an experiment on an Italian corpus. In Proceedings of the 2024 Workshop on Quantum Search and Information Retrieval (QUASAR '24). Association for Computing Machinery, New York, NY, USA, 25–30. https://doi-org.libweb.lib.utsa.edu/10.1145/3660318.3660325
6. Asitha Kottahachchi Kankanamge Don and Ibrahim Khalil. 2025. Q-SupCon: Quantum-Enhanced Supervised Contrastive Learning Architecture within the Representation Learning Framework. ACM Transactions on Quantum Computing 6, 1, Article 6 (March 2025), 24 pages. https://doi-org.libweb.lib.utsa.edu/10.1145/3660647
7. Sinha, A., Macaluso, A. & Klusch, M. Nav-Q: quantum deep reinforcement learning for collision-free navigation of self-driving cars. *Quantum Mach. Intell.* **7**, 19 (2025). https://doi-org.libweb.lib.utsa.edu/10.1007/s42484-024-00226-4
9. Xiao, T., Zhai, X., Huang, J. *et al.* Quantum deep generative prior with programmable quantum circuits. *Commun Phys* **7**, 276 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s42005-024-01765-9
10. Yanan Li, Zhimin Wang, Rongbing Han, Shangshang Shi, Jiaxin Li, Ruimin Shang, Haiyong Zheng, Guoqiang Zhong, Yongjian Gu, Quantum recurrent neural networks for sequential learning, Neural Networks, Volume 166, Pages 148-161, (2023) https://doi.org/10.1016/j.neunet.2023.07.003

Secondary Sources

16. Marcello Benedetti, Erika Lloyd, Stefan Sack and Mattia Fiorentini, Parameterized quantum circuits as machine learning models, Quantum Science and Technology, Volume 4, Number 4, Published 13 November 2019. https://doi.org/10.1088/2058-9565/ab4eb5
17. Jerbi, S., Gyurik, C., Marshall, S.C. *et al.* Shadows of quantum machine learning. *Nat Commun* **15**, 5676 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s41467-024-49877-8
18. Sha, M., Rahamathulla, M. Quantum deep learning in Parkinson's disease prediction using hybrid quantum–classical convolution neural network. *Quantum Inf Process* **23**, 383 (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s11128-024-04588-3

19. Hu, F., Khan, S.A., Bronn, N.T. *et al.* Overcoming the coherence time barrier in quantum machine learning on temporal data. *Nat Commun* **15**, 7491 (2024). https://doi.org/10.1038/s41467-024-51162-7
20. Alona Sakhnenko, Julian Sikora, and Jeanette Lorenz. 2024. Buildung Continuous Quantum-Classical Bayesian Neural Networks for a Classical Clinical Dataset. In Proceedings of Recent Advances in Quantum Computing and Technology (ReAQCT '24). Association for Computing Machinery, New York, NY, USA, 62–72. https://doi-org.libweb.lib.utsa.edu/10.1145/3665870.3665872
21. Archisman Ghosh and Swaroop Ghosh. 2024. The Quantum Imitation Game: Reverse Engineering of Quantum Machine Learning Models. In Proceedings of the 2024 Workshop on Attacks and Solutions in Hardware Security (ASHES '24). Association for Computing Machinery, New York, NY, USA, 48–57. https://doi-org.libweb.lib.utsa.edu/10.1145/3689939.3695783
22. Rosa-Remedios, C., Caballero-Gil, P. Optimizing quantum machine learning for proactive cybersecurity. *Optim Eng* (2024). https://doi-org.libweb.lib.utsa.edu/10.1007/s11081-024-09934-z
23. Zoufal, C., Lucchi, A. & Woerner, S. Quantum Generative Adversarial Networks for learning and loading random distributions. *npj Quantum Inf* **5**, 103 (2019). https://doi.org/10.1038/s41534-019-0223-2
24. Hoch, F., Caruccio, E., Rodari, G. *et al.* Quantum machine learning with Adaptive Boson Sampling via post-selection. *Nat Commun* **16**, 902 (2025). https://doi-org.libweb.lib.utsa.edu/10.1038/s41467-025-55877-z
25. Shinde, U.U., Bandaru, R. Re-locative guided search optimized self-sparse attention enabled deep learning decoder for quantum error correction. *Sci Rep* **15**, 3615 (2025). https://doi.org/10.1038/s41598-025-87782-2
26. Liu, Y. Superconducting quantum computing optimization based on multi-objective deep reinforcement learning. *Sci Rep* **15**, 3828 (2025). https://doi.org/10.1038/s41598-024-73456-y
27. Huang, Y., Che, L., Wei, C. *et al.* Direct entanglement detection of quantum systems using machine learning. *npj Quantum Inf* **11**, 29 (2025). https://doi.org/10.1038/s41534-025-00970-w
28. Choi, S., Salamin, Y., Roques-Carmes, C. *et al.* Photonic probabilistic machine learning using quantum vacuum noise. *Nat Commun* **15**, 7760 (2024). https://doi-org.libweb.lib.utsa.edu/10.1038/s41467-024-51509-0
29. E. W. Bethel et al., "Quantum Computing and Visualization: A Disruptive Technological Change Ahead" in IEEE Computer Graphics and Applications, vol. 43, no. 06, pp. 101-111, Nov.-Dec. 2023, doi: 10.1109/MCG.2023.3316932.

30. A. Chalumuri, R. Kune, S. Kannan and B. S. Manoj, "Quantum–Classical Image Processing for Scene Classification," in *IEEE Sensors Letters*, vol. 6, no. 6, pp. 1-4, June 2022, Art no. 7002004, doi: 10.1109/LSENS.2022.3173253.
31. Lu, S., Braunstein, S.L. Quantum decision tree classifier. Quantum Inf Process 13, 757–770 (2014). https://doi.org/10.1007/s11128-013-0687-5

Foundational Reference Sources

4. Preskill, John, Quantum Computing in the NISQ era and beyond detection. Quantum 2, 79 (2018). https://quantum-journal.org/papers/q-2018-08-06-79/
8. Aram W. Harrow, Avinatan Hassidim, and Seth Lloyd, Quantum Algorithm for Linear Systems of Equations. Phys. Rev. Lett. 103, 150502 – Published 7 October, 2009. https://doi-org.libweb.lib.utsa.edu/10.1103/PhysRevLett.103.150502
16. Masahide Sasaki and Alberto Carlini, Quantum learning and universal quantum matching machine, Phys. Rev. A 66, 022303 – Published 6 August, 2002. https://doi-org.libweb.lib.utsa.edu/10.1103/PhysRevA.66.022303
17. Lloyd, S., Mohseni, M. & Rebentrost, P. Quantum principal component analysis. *Nature Phys* **10**, 631–633 (2014). https://doi.org/10.1038/nphys3029
18. Patrick Rebentrost, Masoud Mohseni, and Seth Lloyd, Quantum Support Vector Machine for Big Data Classification, Phys. Rev. Lett. 113, 130503 – Published 25 September, 2014. https://doi-org.libweb.lib.utsa.edu/10.1103/PhysRevLett.113.130503
19. Iris Cong, Soonwon Choi, Mikhail D. Lukin, Quantum Convolutional Neural Networks, Nature Physics (2019). https://doi.org/10.1038/s41567-019-0648-8
20. Jonathan Allcock, Chang-Yu Hsieh, Iordanis Kerenidis, and Shengyu Zhang. 2020. Quantum Algorithms for Feedforward Neural Networks. ACM Transactions on Quantum Computing 1, 1, Article 6 (December 2020), 24 pages. https://doi.org/10.1145/3411466

Appendix B – Annotated Bibliography

Date	Paper Title
6 August, 2002	**Quantum learning and universal quantum matching machine**
	Early work examines a 'matching' problem where an input is evaluated to determine what state it most closely matches
	This is done to demostrate that quantum computers can perform maching learning, aka learning a model from training data and then matching unseen information
	The problem uses three different quantum states that are pure qunatum states with an unknown phase shift applied to them
	The template (training data) state is the tensor product of the three pure states with unknown phase shift applies
	For simplicity, the states have just two classifications, but they could be any number of states.
	Two solutions are offered, a semi-classical Bayesian classifier and a universal quantum matching machine
	For the semi-classical, strategy is to use state estimation on the templates, then use results to create classifier, then measure and apply classification
	The universal quantum strategy attempts to learn the state without the initial state estimation from the semi-classical method
	This is done by utilizing the probability distributions of the input features. The probability is used to create a score for each state that will be maximized
	The task is to find the positive eigenvalues resulting from comparing the template data to the new state data
	This information reveals how similar the new state is to one of the classifier states
	Paper also considers difference between only having a single copy of the new state and the theoretical infinite number of copies

	This is important because quantum computing has a 'no cloning rule' and states must be constructed, not copied. It may not be possible to create multiple copies of test data
	Understandably, scores were improved on multiple copies of the data rather than just a single instance
7 October, 2009	**Quantum Algorithm for Linear Systems of Equations**
	The study authors show that Quantum computing can be used to create a solvable system of linear equations.
	Given a hermitian matrix A and vector b, want to find a vector x such that Ax= b
	vector b can be encoded on quantum state |b>, then hamiltonian of A can be applied to |b> which is a phase transformation
	|b> can be decomposed into eigenvalues, then normalized
	If eigenvalues are too far apart, A cannot be inverted. ratio between smallest and largerst eigenvalues is k. singular values of A need to be between 1/k and 1.
	System results in vector x. However, in quantum you cannot read all values of x unless you run the process n times for the n values in vector x.
	Better approach is to use expectation value x^TMx where M is a linear operator.
	From M, features of vector x can be extracted.
	Why does this matter? A system of linear equations in machine learning is several equations that use the same variables and can be solved to find the values of the variables.
	Having a system of linear equations in a quantum system makes it is possible to minimize or optimize these given variables.
	Additionally, an exponential speedup of solve the SLE occurs compared to the classical SLE
	Overall runtime is O((log N)k^2s^2/e) where s is the number of values in a row of the spare matrix and e is error

	Clearly, if some constants such as the eigenvalue ratio k is large or the matrix is not sparse then the runtime will suffer, but poly O(log N) is a speedup over the linear N of the regular SLE
01 March 2014	**Quantum decision tree classifier**
	A decision tree classifier is a ML method for supervised learning where regression is used to split data into subgroups
	decision tree needs to create optimal tree splitting decisions with minimal error and then using the tree to accurately predict class of unseen objects
	The paper adapts classical decision tree algorthm into quantum computing, authors are designing a classifer that handles muliple class labels
	Separately, there is a quantum oracle (referred to as a quantum query) algorithm that returns values based on a predetermined function. The function does not learn and is not considered a decision tree
	Splitting a decision tree requires a metric to decide, here the quantum entropy or Von Neumann entropy is calculated and used.
	A quantum entropy of zero indicates a pure node which is the ideal splitting state.
	Quantum mechanics has a no cloning rule which does not allow data to be copied. Everytime a calculation is needed, a specific superposition must be created.
	For the decision tree classifier, the paper's authors are not strictly adhering to this. They are allowing multiple copies of training and test data to exist. The number of required copies is not calculated
	The Node Splitting algorithm takes the quantum entropy value of a random node and searches other nodes for a lower value. If none is found, the node with the lowest entropy is returned.
	The node splitting algorithm uses Grover's Algorithm for this process. Grover's is actually used in several of these decision tree classifier algorithms.
	Grover's uses a quantum oracle to differentiate between inputs and them amplifies their amplitudes to increase the probability of identifying the desired state.

	In order to partition data using attributes, the data distribution is predetermined. It is then sorted classically, as a quantum sorting is more expensive. O(n log n) classical vs O(2/3n^3/2) quantum
	Next the fidelity of the quantum state of the data distribution is measured. The fidelity measurement is the measurement of the closeness of the angle between quantum states.
	The data is then clustered by first comparing the fidelity of all pairs of states and creating a cluster for each found state. For all points grouped together, a centroid is calculated.
	The second step of the clustering algorithm is to take all points that were not assigned to a group and assign them to the group with the nearest centroid.
	Now that groups have been created, the decision tree may be constructed by selecting groups and calculating quantum entropy. The split occurs where the entropy is smallest
	Final output of the quantum decision tree is a sorted list by fidelity. Searching list can be done with Grover's algorithm
	Authors point out that Quantum model still lacks many features of classical decision trees (eg node pruning, training data with quantum noise)
	This work is entirely theoretical and was not tested on quantum hardware. The runtime of the algorithm benefits from the speedup of Grover's as it is used frequently
	That said, the state of quantum technology in 2025 is not such that this can be put into practice.
	To elaorate, The state of NISQ hardware is such that there would need to be tomography used to keep the data in an intermediate state or run into decoherence issues.
	The authors also acknowledged that they didn't look into errors which seem likely given the complexity of the algorithms versus the limited circuit depth that can work on today's hardware.
27 July 2014	**Quantum principal component analysis**
	Classical PCA is a technique that identifies variance within data by mapping it onto a lower dimension space

	Quantum Tomography is a method of measuring a quantum state to discover features of the quantum state.
	Tomography works with multiple copies of the quantum state to draw necessary conclusions
	However, instead of treating the state in tomography as a passive thing, we can convert it into an energy operator or Hamiltonian
	The quantum state or density matrix is used to calculate eigenvalues and eigenvectors
	Makes it possible to construct the large eigenvectors and eigenvalues of the state which are the principal compontents. Thus, quantum PCA has been performed.
	Would need one density matrix/copy of the state per dimension of PCA analysis that you are interested in.
	PCA process runs faster with a matrix that is well represented by just a few principle components. Holds true in both classical and quantum
	This is a roundabout way of saying that it works best with low rank matrices.
	The principal compnent matrix can be calculated in O(log n) when the data in the matrix is sparse.
	The quantum hardware can store the coefficents of the vectors in O(d) hardware/qubits where d is the dimensionality that we have reduced the analysis to.
	Further any matrix can be exponentiated in O(log d) time with this method. Authors need access to vectors A in AA^T to make this happen.
	Adding in another term, quantum PCA runs in O(R log d) time while classical PCA runs in polynomial (quadratic) time. This is the quantum speedup of quantum PCA.
	Paper is proving the theory behind the calculations. It did not run any simulations
	Quantum PCA still limited to a fraction of information available in classical PCA because of challenges in getting large amounts of classical data into quantum systems
25 September, 2014	**Quantum Support Vector Machine for Big Data Classification**

	Classical SVM is a supervised ML technique, splitting data into groups based on the best linear fit
	Quantum SVM implemented with O(log NM) for both training and running time where M is data points and N is features
	Utlizes least squares as SVM solving technique for solving with quantum phase estimation
	The quantum SVM process uses the quantum PCA matrix exponentiation method to speed up calculations
	For the process of translating the kernel matrix in SVM to quantum computing, the authors propose an oracle to return the kernel calculation
	An oracle is a 'black box' type of function that can receive a query and give an output but otherwise has no parameters for tuning.
	Speedup is achived through inner product evaluation of matrices, calulated in O(log N) in quantum environment, but polynomial time classically.
	The algorithm works by creating a quantum state that describes the hyperplane using the matrix inversion algorithm and the classifies a given quantum state vector
	When trained, the quantum SVM can act as a new computational basis for testing, with the basis aligned with the training labels.
	For classification, construct a state with equal probability of the test vector and the basis state, then measure the ancilla of state to construct success probability P
	If P < 0.5 then test vector is classified as +1, otherwise it is -1
	Quantum SVM may also provide some measure of privacy as the data from calculations doesn't have to be fully represented, only inner product
	Also, once the kernel matrix is generated the data is hidden from the user.
	As with quantum PCA, this work is done as a proof and is not implemented. It may be impossible to implement on today's NISQ hardware

	Similarly, it's good to recognize that there may be some privacy benefits, however, given that you cannot store quantum information for any period of time, that benefit may be short lived.
30 July 2018	**Quantum Computing in the NISQ era and beyond**
	Although it mentions QML/deep learning, this is not specifically about quantum machine learning. It does discuss what's feasible in quantum research given 2018 technology
	This work matters because machine learning algorithms have to run within the environment that was detailed here. Although developments have happened over last 7 years, framework remains relevant.
	Looks at the entanglement frontier, largely meaning that we're devloping tools (quantum hardware) to explore quantum systems.
	Utility of quantum devices will come from quantum complexity (gain from using superposition) and quantum error correction (ability of hardware to maintain accurate state)
	Potential of quantum algorithms? Possibly solving problems difficult for classical computers. Primarily Shor's factoring but not a lot else as of yet
	More potential-- Complexity allows speedup because superposition allows multiple problems to be factored at once
	More potential-- We can't (fully) model quantum systems on classical systems. That should be reason to be optomistic about potential
	Unlikely to solve classically NP-hard problems, most likely to speed up exhaustive search of them. May also improve on approximation algorithms of NP-hard problems
	Quantum challenges- systems need quantum particles isolated from other things to work, but must be connected externally to get input and send results.
	Error Correction necessary to scale up quantum computers from current state to more realiable state

	Current hardware state term coined NISQ - Noisy Intermediate-Scale Quantum- Noisy means control of qubits imprecise, intermediate scale means 50 to a few hundred qubits
	Best technologies for qubits are trapped ion and superconducting processors. Error rates still high on these 'best' technologies
	Notes that even though quantum computers are improving, classical are as well so quantum advantage over classical may continue to be a moving target
	Quantum annealing alternate technology with lots of qubits and low noise, however, untested at scale.
	On the machine learning topic, as of 2018 it was mostly theretical, needed more testing. Aside from purely focusing on speed ups, QML research may yield improvements in classical algorithms too. TBD.
	There isn't an easy way to move large amount of data from classical to quantum so encoding large amounts of date in qRAM/quantum registers has high overhead.
	Mentions HHL System of Linear Algebra article cited previously, calls it BQP-complete because any problem solved efficiently on a quantum computer can be encoded as a matrix inversion problem.
	Although nearterm improvements to hardware are expected, it is extremely unlikely nearterm that things will scale to the point that large circuits are feasible on quantum computers (correct for 7 years later)
26 August 2019	**Quantum convolutional neural networks**
	Given advances in classical ML, want to see if these can be translated to quantum computing
	Two quantum problems have the potential for investigation, Quantum Error Correction, applying optimal code given an unknown error model
	and also Quantum Phase Recognition, determining if an input quantum state belong's to a particular quantum phase.
	These are hard to accomplish without resorting to the difficult/expensive process of quantum tomography

	Additionally, state of quantum hardware limits depth / complexity of quantum algorithms
	Quick classical CNN summary- Convolution layers create feature map, pooling layers condense map to smaller grid, final layer is classification with some activation function
	Hyperparameters like number of layers, size of weight matrix are usually fixed for a given CNN
	Translating this to quantum, the convolution layer is where a single unitary operator is applied
	The for a pooling layer, some of the qubits are measured and the result specifies how much rotation is applied to nearby qubits
	quantum convolution and pooling are repeated until size is sufficiently small. For a fully connected layer, another unitary operator is applied.
	Final output is obtained by measuring a few qubits. The hyperparameters (num of layers) are fixed, the unitary operators are learned.
	One practical application of this is a multiscale entanglement renormalization ansatz (MERA).
	MERA takes an input state and adds a new qubit to and perfoms a unitary operation on all of the data.
	As MERA is adding qubits and the CNN convolution / pooling layers are shrinking the number of qubits, a circuit can be created where MERA runs in one direction and CNN the other.
	Athough the logical layout is symmetrical in the reverse, not every CNN step has to shrink / remove qubits although the MERA process does always add qubits.
	What can be done with the extra unneeded qubits? They can be read as part of error correction where the quantum error correction does syndrome detection
	It's at this point where we can be sure that this is a simulated environment. As of 2019 there was not a functional QEC model where it performed better than the physical error rate

	Even though it is simulated, a reasonable (for state of NISQ hardware) two layer QCNN with N=9 qubits was modeled. This system had 126 parameters.
	This model was used in simulations where x-axis, y-axis, and z-axis errors were correlated and uncorrelated. It was then compared to Shor's QEC error correction
	Shor's QEC assumes no correlation between errors and the QCNN performed the same when there was no error correlation.
	QCNN performed better than Shor's QEC when errors were correlated, however, there are no studies that suggest quantum errors are correlated. That doesn't prove they aren't, of course.
02 October 2020	**Quantum Algorithms for Feedforward Neural Networks**
	Starts with overview of classical neural networks, mentions importance of back propagation. Notes that neural networks require significant resources to train and run.
	Quantum challenges: neural network computations are very sequential, quantum computing is very parallel. Quantum computing also challenged by intermediate step calculations.
	Further: Strength of neural networks comes from non-linearity. Quantum relies heavily on linear algebra. Quantum requires many extra steps to handle non-linear calculations.
	If training a NN on quantum computer, parameters and training data must be encoded into quantum states. State preparation can be a bottleneck for quantum computers
	Not all bad. classical NNs use a lot of linear algebra despite non-linearity. Randomness is common in quantum computing and many classical algoritms make use of some randomness as they are optimized.
	Solution for non-linearity is to store vector inner product data in qRAM instead of quantum states. non-linear calculations can be performed on qRAM.
	Some things like a weight matrix is too large to be stored in qRAM, quantum states can be reconstructed indirectly
	Side note: There are several "Quantum Inspired" algorithms that have been developed to run on classical computers featuring "only" a polynomial slowdown in running time. Paper dryly notes how that might matter.

	Proposed quantum feed forward algorithm has not been proven to work better/faster than classical counterparts.
	Quantum training part of the process is stated to have polylogarithmic time. Paper also states that logarithmic term dominated by other factors, effectively is O(((TM)^1.5)N) where
	T is number of update iterations, M is size of minibatch, and N is total number of neurons in network.
	Quantum evaluation also has a logarithmic term that authors state is minimal leaving us O(N) where N is still the count of neurons.
	Contrast this to classical where training is O(TME) {new term E is edges} and evaluation is O(E). Paper also notes that classical NN have lots of edges.
	paper summarizes classical CNN calculations then contrasts with quantum where the inner products in forward and backward propagation steps are estimated (within an error tolerance) rather than calculated
	Returning to discussion of quantum training, it is a hybrid classical - quantum setup that only uses quantum to estimate inner products and to move data in and out of qRAM
	The paper discusses qRAM in a different way than most quantum papers which usually describe it as a quantum register or set of qubits. Here, the data is stored in a binary search tree.
	To expand, the paper assumes the qRAM is fully error corrected and notes that this is far off from what is available on today's NISQ hardware. Fault tolerant quantum computing would be a huge milestone.
	A presentation of the algorithms for forward and backward propagation are presented. They include the inner product estimation. The algorithms are then simulated classically.
	Because they are simulated classicaly, we do not get a speed up, hence the earlier side note. The quantum NN performs better than classical on the IRIS dataset when the error is 0.1. Much worse for other error values.

	The error estimation is compared to classical algorithms that introduce noise to effectively combat overfitting.
	Paper is very clear that classical algorithms outperform this method currently. The authors believe the inner product estimation where it effectively fights overfitting without additional steps is promising for future work.
	Finally, quantum feedforward neural networks are presented as theoretical, with the suggestion that the quantum inspired version is helpful for designing future algorithms.
07 December 2021	**Quantum deep reinforcement learning for clinical decision support in oncology: application to adaptive radiotherapy**
	Heathcare background: Radiation Therapy is a common cancer treatment, ~29% of cancer survivors in 2016 received some form of RT
	Radiation Therapy sessions (in terms of radiation dosages) are similar for patients with the same stage of cancer
	It is also known that patients do not all respond the same way to radiation therapy as a result of biological variation
	Therefore, a one size fits all approach to radiation will be suboptimal, personalizing radiation dosages is expected to imrpove outcomes
	Study examines treatment of lung cancer patients, they will all be treated the same for four of the six weeks of therapy with a custom plan for weeks 5 and 6.
	Reinforcement learning is a machine learning technique where the model is rewarded for making positive decisions. Tuning occurs over several iterations
	Reinforcement learning is here applied to radiation dosages using a Bayesian Network for feature selection
	Approach also incorporates prior knowledge into the process in addition to patient dosage information
	Deep-q reinforcement algorithm is used, specific configuration of deep-q for cancer treatment not discussed in paper.

	Output from Deep-q is encoded into quantum states. Highest state value selected and amplified, resulting in dosage measurement.
	Dosage is then simulated (rather than being used in actual practice) in reinforcement learning model which predicts the patients next state
	Quantum aspect of the model is designed to simulate the uncertainty in decision making process
	Authors state that their study is similar to a 2020 study using Quantum Reinforcement Learning involving gambling decisions. Main difference is Deep-q algorithm
	Compared 3 models, plain quantum reinforcement learning, quantum deep-q reinforcement learning simulated in qiskit and results run on actual IBM quantum circuits
	Had AI decision making, rewarded positive outcomes which were specific local tumor control and no raditaion induced pneumonitis.
	AI always selected highest score in these areas effectively making them confidence scores
	This was not supervised learning, so authors created a similarity score to compare typical practices and a self evaluation score to compare model to actual clinical decisions found in patient data
	When comparing model recommendations to actual recommendations, authors had to label some outcomes as 'unclear'
	This is due to the fact that patients experiencing pneumonitis in the actual real life results may or may not have been able to tolerate higher dosages simulated and recommended by model
	Quantum methods showed up to 10% improvement on clinical decisions
	Also, the simulator and the actual IBM quantum hardware performed differently. Authors had to design the circuit differently to avoid decoherence
	Authors also mention that they could not use the true Grover's quantum amplification method on the IBM hardware becuase of circuit depth/decoherence issues

10 January 2022	**Parameter estimation in quantum sensing based on deep reinforcement learning**
	Physical quantum systems require regular upkeep to maintain functionality. Systems make readings using sensors that must be regularly calibrated.
	Paper investigates the process of qunatum sensing and the methods to find the best system parameters
	Background: Sensing follows general workflow: 1) Prepare probe state, 2) Apply quantum transformation [Hamiltonian or Gate] 3) Measure new state
	Convential methods for determing sensing parameters are GRAPE and CRAB which are both sensitive to noise and are reportedly hard to engineer
	Machine learning has been previously used to create optimal parameters for time independent processes
	Authors are exploring whether some techniques can also be applied in time dependent setups (meaning where decoherence of data is an issue)
	The specific time dependent use case is time-dependent Hamiltonian evolution, where an unknown parameter influences strength of Hamiltonian
	Sensing is key to quickly determining unknown parameter
	In noiseless environment, this unknown parameter has an upper bound and reinforcement learning is used to treat the difference between upper bound and actual as reward term.
	There is an agent which feeds improved terms into the system to calculate the system parameters
	A classical deep reinforcement process' output is used to create a quantum ansatz used in an QVE / eigensolver algorithm
	The output creates better possible eigenvalues for the problem
	This is slightly different than the idea of using quantum computers to speedup or otherwise improve on the performance of classical algorithms. It's using classical algorithms to improve quantum computing.

10 May 2022	**Quantum–Classical Image Processing for Scene Classification**
	Image augmentation performed by a quantum computer.
	Satellite images are reviewed and enhanced through a hybrid ml and quantum model
	Only needed 4 qubits for this model which is good for NISQ hardware
	The research from this paper was used in the Q-SupCon model to augment image sets and increase the accuracy of classifications
05 January 2023	**Quantum Fourier Convolutional Network**
	Paper notes that convolutions and quantum have similarities at a surface level (both perform matrix operations in high dimension vector space) and look to see if quantum advantages can be applied to CNNs
	Direct convolution of a quantum state is not possible, however, authors propose hybrid approach as a workaround
	Training time in deep learning is a burden, anything that can reduce overall training time (such as speeding up computations) is worthy of exploration
	Replaces the discrete Fourier transform in CNN with quantum Fourier transform to achieve speedup over classical
	Simulated models (again, not actual) run faster with quantum CNN over classical
	In the construction of the quantum fourier transform, authors discuss 'qRAM' which appears to be a quantum register set aside for a quantum state to be saved. It's more like loaded and briefly held than truly 'saved'.
	In terms of background, qRAM which is also sometimes called a quantum register, is a series of physical qubits can be organized into a logical space.
	The overall process has the kernel being applied to one register and the input vectors (from perhaps an image) being applied to another register.
	The registers are then multiplied togetherin such a way that the result of the operation is the inverse quantum fourier. It is then sent to back to a classical computer to continue classical CNN computation

	The quantum foruier transform takes the same inputs as theclassical discrete fourier transform
	Needs n(n+1)/2 gates to perform QFT on n qubits. Quadratic can scale up quickly. 10 gates for n=4, 36 gates for n=8.
	Time complexity improves from O(n2^n) for classical to O(n^2) QFT.
	Backpropagation is a challenge in quantum circuits. Because of the parameterized circuits, gradients can be calculated by running cicuit again with shifted parameters
	Ran the QFCN as a simulation on the MNIST dataset. Noise was simulated as well to make it similar to real life quantum hardware
	In the simulations, the QFCN compares well with a control non-fourier Quantum CNN model constructed for comparison
	Authors show that it is possible to take advantage of quantum speedup in CNN calculations.
7 Feb 2023	**Quantum Recurrent Neural Networks for Sequential Learning**
	Authors want to design a Quantum Recurrent Neural Network that's realistic for the NISQ hardware environment that exists in today's quantum world.
	An approach to the quantum circuit where all QRNN circuits are run one after another, modeling the classical RNN directly will unfortunately have decoherence problems on today's hardware.
	The paper works around this issue by proposing a staggered QRNN circuit.
	It's helpful to review what a classical RNN is. It is similar to CNN, however R is for recurrent and is used for sequntial/temporal data
	The classical recurrent network uses a function that takes the input from the most recent item in the time series and combines it with the output from the last step/layer to create an updated output.
	That last layer output in the classical RNN implicitly contains output from all of the previous layers because the function works recursively in that manner.

	A common bottleneck for classical to quantum algorithms is the encoding of classical data into quantum qubits
	Amplitude encoding is a commonly used method to encode exponential classical bits into quantum superpositions, downside is that quantum circuits grow exponentially with datapoints
	Angle encoding of classical data takes the datapoints and represents them as angle rotations around the computational basis. Qubits are just O(n) of classical datapoints. This is more efficient.
	Because more qubits lead to more errors in an NISQ environment, angle encoding is used on data.
	Authors use three qubits for a single classical bit, intentionally redundant because of error issues with NISQ circuits
	An ansatz, which is a parameterized quantum circuit that has adjustable gates is used to perform the work of the QNN
	The values of the gates in the ansatz are what is trained by the model.
	QRNN ansatz must be implemented in a hardware efficient way using single qubit rotation gates and two qubit controlled rotation gates which can be decomposed into CNOT and Rz gates
	For measurement, paper has a reminder about quantum measurement, namely that upon measurement state collapses to one or zero in computational basis, must rerun multiple times
	Multiple runs will give us an estimate of expectation.
	In proposed model, first qubit of register is measured, then converted to prediction term yt
	Paper demonstates what closed system QRNN would look like, with a quantum register that takes a new datapoint and a second register that holds the ongoing value of the variables

	While quantum register with new data is reset prior to each input, the other register is not reset during the process. It has to hold the state for many iterations, which is unlikely to hold in an NISQ open system
	In the proposed staggered model, only two of the three qubits holding the state must remain for the next iterations, paired with one of the qubits that was previously used for new data.
	Each time a new datapoint is processed, the two registers shift by one qubit each. This means the state registers are all reset every 3 iterations, making that the longest time that a qubit must maintain coherence.
	Just as in classical deep learning, predictions are optimized versus real values. The authors used least squares
	Unlike classical machine learning, backpropagation cannot be computed because that relies on saving the state of the environment, an impossibility in quantum computing
	An approximate derivative can still be calculated on the qunatum computer, it requires running the quantum circuit twice with slightly different values and taking the difference between the loss functions
	Additional derivation steps must be computed on a classical computer.
	Performance of two QRNN systems (called plain and staggered) are then compared to a classical RNN that is configured similarly to the QRNN setup.
	The circuit was based on seven days of input data then used to generate a prediction. The RNN model was the same for comparison, the authors did not discuss if this was the optimal RNN configuration
	The two quantum RNN models performed similarly to the RNN on actual data and were even more accurate for a few features such as wind speed in meterolgical data.
	Having larger redundant registers of qubits was also studied. Prediction accuracy increased as quantum registers grew from 4 to 6 to 8 qubits. Again, the registers are holding redundant information
1 November 2023	**Quantum Computing and Visualization: A Disruptive Technological Change Ahead**
	Excellent and compact summary of quantum computing

	Article is about improving Bloch sphere represenetation by means of a QC sphere that shows weighted probabilities of superpositions
	Useful for introductory information, the rest of the content is not relevant to quantum machine learning.
11 December 2023	**A survey on the complexity of learning quantum states**
	The survey examines multiple different quantum computing problems and recent advances
	Learning here is on the broad side for quantum machine learning, for example, one section examines whether you can learn the physical state of qubits
	There is more discussion on advanced topics such as learning about classical functions encoded into models
	May want to examine some of the cited articles for further research.
08 January 2024	**Deep Q-learning with hybrid quantum neural network on solving maze problems**
	One option is to create a quantum walk algorithm and a variational quantum circuit (VQC) to encode classical agents with state information. Second option is to use a fully quantum VQC.
	Fully quantum model promising, but hampered by state of NISQ hardware
	Briefly discusses classical reinforcement learning using a reward signal, specifically Markov decision making process (MDP) investigated
	In MDP, agent observes state, then selects action and receives a reward based on the desirability of the action. The process repeats at the next state and the agent is expected to optimize reward.
	quantum approach uses a 'model free' method of estimating state-action pairs and then using that estimate to update the value with a paramaterized (VQC).
	The model free method is referred to as Q-learning as the model estimates a Q-value or cumulative reward
	deep q-learning is approximating the q-value/q-function with a neural network

	Experiement constructed for quantum neural network to search 4x4 maze
	Hybrid quantum / classical environment because full quantum not yet practical thanks to noise and scalability issues
	classical agent updates quantum learning table by estimating quantum states and storing them in table
	The agent receives updates from deep neural network, the variational quantum circuit is used as the last layer of the DNN
	To prevent correlation between samples, the agent has past transitions in a table and a random past experience is chosen each time algorithm runs
	Loss function is Q-Loss, which MSE between predicted and target Q-values. For each step the agent caculates new gradients and then updates neural network weights.
	Circuit design uses two qubits which are manipulated by feature encoding and ansatz module to return a result
	Researchers ran the QNN in a simulated qiskit environment and compared results to traditional CNN
	Traditional CNN had a better win rate in 4x4 maze (89% vs 85%) and a much shorter training time (only 1/8th of qNN training).
	qNN improved on 5x5 maze but still was inferior to traditional CNN.
	Researchers suggest that implementing CudaQ for quantum GPU could improve process. Future work oppotunity.
	Although performance strictly worse than classical, study shows that the QNN is feasible, particularly if it can be effictive implemented on real quantum circuits
02 May 2024	**Quantum deep learning-based anomaly detection for enhanced network security**
	web security involves monitoring traffic, finding anomolies and mitigating them.
	Quantum machine learning has not commonly been used for this application. Want to explore quantum's ability to process correlated features

	Proposed frameworks explored include quantum auto encoding plus a one layer SVM, kNN, or Random Forest.
	Anomaly detection has challenges including class imbalance, diverse types of anomalies, and unexpected abrupt behaviors
	Previous work in QML anomaly detection used supervised learning. Here attempting unsupervised learning.
	Autoencoder are used to compress state details while maintaining key information. Noted that it is similar to PCA ML technique.
	The goal of the encoder in this context is to compress quantum information so it can be represented classically.
	Quantum qubits represent 2^n classical bits of information, explaining why it would be necessary to compress information to keep it managable on a classical system
	A six qubit quantum encoder/decoder is presented. When encoded, the full quantum information is conveyed on half (three) of the qubits.
	Authors expect the auto encoder to learn typical patterns so it may detect anomalies
	Using the encoder on its own to detect anomalies soley based on how much error was in the reconstruction of the quantum state was examined and discarded.
	For the proposed model, the classical data is first run through PCA to get it down to a few key dimensions represented by qubits. The expirements used 4 qubits for this
	After the classical PCA, then the quantum autoencoder is used and then one of the three models mentioned earler are applied. The quantum autoencoder is doing more compression from the classical input
	With the one layer SVM, both a fully quantum SVM and a classical SVM were examined.
	With the random forest approach, the input is fed through several variational quantum classifer (VQC) models. The VQC models are trained and a majority vote of the models is taken.
	For kNN, the quantum encoded data of the test state is compared to the nearest neighbors of M training states. Fidelity (similarity) is the metric used in kNN

	The article discusses different methods of constructing the SVM quantum circuit, both methods need 2^n gates per feature which can quickly become large
	For random forest, a feature map circuit and an ansatz circuit are designed.
	Test are performed on several different anomaly detection datasets. It's noted that as a succes metric, accuracy is not useful because of class imbalance in anomaly datasets. F1 score used for evaluation
	KNN method performed the best of proposed frameworks. Authors believe that it is because of the distance/fidelity metric used for anomaly detection.
	Expirements were simulated using pytorch and qiskit
	Tests were performed on actual quantum hardware, notable because many QML just do simulation. Still won't be replacing classical ML soon.
07 June 2024	**Study on The Effect of Encoding Method in Quantum Machine Learning**
	Encoding is important to consider in quantum computing because of all the data that must be encoded from classical to quantum
	Method of encoding data is important because of the quantity of data ingested by models and the provides an upper limit on performance of quantum models
	Enoding options include amplitude encoding and qubit rotation
	Previous work has shown that choice of encoding method results in different decision boundaries.
	Want to quantify the results from encoding. Have come up with distribution distance and distribution radius based on geographic distance in Hilbert space
	Distance conveys how well enoded the points are and the radius shows how close they are to the mean.
	Paper examines binary classification in supervised learning where data is appropriately split into one of two classes
	The mechanics of translating cartesian points onto a Bloch sphere representation are discussed.

	Cosine distance is preferred over euclidean distance because euclidean distances become similar in high dimension spaces.
	There is a relationship between distribution distance and distribution radius. Models preform better with a larger distribution distance and smaller distribution radius. (Well defined and tightly clustered)
	There is also a relationship with accuracy. With fixed radius, accuracy increases as distance increases. With fixed distance, accuracy increases as radius decreases.
	The authors do not state one encoding method is superior to another. The framework of distribution distance and radius can be used for evaluation in any specific instance.
	Only examined a single qubit. Haven't investigated multiple entangled qubits, possible topic for future work.
11 June 2024	**Learning Shallow Quantum Circuits**
	Advantages to using quantum shallow circuits: shallow quantum circuits more powerful than classical,hard to simulate on classical, works in NISQ environment
	No previous polynomial time algorithm defined for learning shallow quantum circuits. Challenges for learning include lots of bad local mimima and the fact that common algorithms like gradient descent fail.
	Parameterizing the gates, like making an ansatz, makes it possible to train a quantum circuit and make it possible to do Quantum Machine Learning.
	Deep neural networks in quantum are challenging because of 'barren plateaus' which is really gradients that become zero and drop out/cause learning to cease
	Therefore, shallow networks should have an advantage. They still have lots of local mimima during optimization.
	Quantum tomography is resource intesive and scales poorly, however, the best case for using it is when the scale is small like what you have in shallow networks
	Proposed technique is to have qubit inversions to disentangle. Can lead to complete circuit without difficult

	Setup: Let unitary U have n qubits. Take randomized dataset with N samples. Each N sample represents an input state and a pauli output measurement.
	Theory: When circuit is over finite gate set, U can be learned with O(log n) samples and poly (n) time
	Note that polynomial time has a large exponent. There is further theory that this can be refined b/c modern hardware uses geometrically local circuits
	with that, it becomes learned in O(log n) samples in O(n log n) time and learned circuit depth of (k+1)(2d + 1)+1. k and d are dimensions of the quantum lattice
	These theories can formalize the circuits as quantum celluar automata (QCM)
	Finally, circuits can be learned with O(1) queries in O(n) time. [NB, these are tightly bound big theta]
	Does this extend to higher depth circuits? No. Must use Grover's algorithm and then will be bounded by runtime/complexity properties of Grover's
	Why is small depth important? Because by using local inversions, we're brute force checking if UV' = U' [tensor prod] I for some n-1 qubit U'.
	The larger n is the larger the search space which will become impossible to manage at large n. Hence, switching to Grover's
	Also key to the process is the locality of the gates. Swap opeations are performed for the inverse. If the gates are not local, more swaps have to be completed, leading to (much) higher error.
	Finally one step to learning circuits it to disentangle them. Can be done by checking for inversions in O(nC) time where C is the maximum number of inversions for region.
	Given that larger depth models lead to high error rates on NISQ hardware, exploring this learning complexity for shallow circuits is useful for understanding tradeoffs in circuit design
20 June 2024	**Deep Ensemble learning and quantum machine learning approach for Alzheimer's disease detection**

	Alzheimer's disease is debilatating mental illness. Study investaged use of patient MRI scans to look for Alzheimer Disease markers. This data set is available through Kaggle.
	Model used combined VGG16 and ResNet50 to extract features. Features were then fed into QSVM model which gave classifications.
	There are a number of deep neural networks that have been created to solve this problem in related work section. A 2023 model reportedly achieved 99.68% accuracy, which is state of the art.
	VGGNet has nine convolutions, two batch normalizations, three max-pooling, two dropouts, and one flattened layer.
	ResNet 50 model has one convolution, one max-pooling, one average polling, one batch normalization, one activation, two identity blocks, three conv blocks, and one flattened layer.
	Flattened layers from each model are concatenated and fed into QSVM. Dataset was reduced to 5 dimensions so as to only need 5 qubits in the SQVM.
	Data augmentation was also performed on the dataset to combat class imbalance and overfittng.
	The classical SVM scores were lower than 'related work' state of the art SVM. Authors state this is related to what images they trained the models on, which were not MRI scans.
	Ran through IBM Qiskit simulator, doesn't appear to have actually run code on IBM hardware. Achieves proof of concept but doesn't have quantum advantage in simulator.
	ML + QSVM/Qiskit improved on accuracy/recall precision of classical SVM algoritrm.Metrics for QSVM ensemble model over 99% so they are acceptable.
	Training of classical deep learning models were discussed, however, there was no discussion of actual training qsvm training (even in qiskit).
	Although not evaluated on actual quantum hardware, given the small scope of a quantum SVM, this could plausibly be used, depending on how difficult it is to actually implement.
06 July 2024	**Shadows of quantum machine learning**

	Discusses 'shadow' models or models trained on quantum computers and evaluated (inference step) on classical computers
	This addresses access bottleneck in quantum computing at a tradeoff of speed at evaluation time.
	Typical ML workflow is training phase on training data followed by inference phase on test data. Quantum computing is needed at both steps for QML. Access to quantum computers very limited right now.
	Shadow tomography (recreating qunatum state) can be used to create a classical model after the training is complete.
	Seek answers to the question of whether there is still an advantage in a classical but quantum trained algorithm. Also, are there quantum algorthms that can't be converted to classical
	Shadow algorithm draws from linear algebra, where the trained f(x) function is a trace of the quantum density matrix for the parameter theta (generally a Pauli rotation)
	Shadow model is a flipped version of the quantum model. Specifcally, the quantum model has an encoding state followed by a paramerized function.
	The filliped version starts with the parameterized function followed by the encoding step followed by observations. A bit string is generated following this.
	When the model is evaluated multiple times, the set of bit strings is then used as input or "advice" to the classical algorithm along with the new test input during evaluation.
	There is not a discussion of the methods of shadow tomography as other papers cover this topic. It is noted that the choice of method may force limitations on shadow function.
	Have to consider what models can be flipped? The parameterized function has to be transformed into a density matrix. Adding a qubit can address the eigenvalues that must be calculated.
	Number of qubits involved in flipping is logarithmic because Pauli observable is 2^n.

	Although classical algorithms do not have a quantum advantage, unless a trapdoor function is given. The 'advice' generated earlier serves as a key for these trapdoor functions
	Specific trapdoor function in this case is the discrete cube root. If you consider how cryptographic functions work, you will have a general idea of how the advice calculation can be a key for the cube root.
	When determining if quantum models have shadow equivalents, it is helpful to rewrite quantum model equation as a fourier series.
	For high dimensional data fourier series can suffer from exponential sample complexity needing 2^n calls to converge.
15 August 2024	**Quantum deep generative prior with programmable quantum circuits**
	Parameterized quantum circuits (PQC) are used in Quantum Machine Learning
	Because of today's NISQ hardware, it's difficult to scale the depth and width of PQC circuits
	One challenge of exploring quantum algorithms is that classical simulators struggle to fully simulate them.
	The authors take on a computer vision task with classical image generation via GAN assited by PQC
	With ghost imaging, a low resolution image is created and the quantum algorithm must reconstruct it.
	Classical CNNs capture image statistics during processing that can be treated as a prior image
	Higher dimension images can be approximated by a learnable generator G that captures latent space Z
	Proposed: Quantum Deep Generative Prior (QDGP) using PQC to generate latent space with larger dimension thanks to quantum capabilities
	Images were created by taking an original image and transforming it into a degraded version. Ghost Imaging priors is using low light (as little as a few photons)

	Reasearch on classical methods to reconstruct degraded images with minimal samples is ongoing, however, they often need large datasets for training which is a challenge
	For experiments, QDGP utilizes a pretrained BigGAN. Tests involved images chosen to be outside of trained dataset
	With small number of samples, quantum models were competitive but inferior. With larger sample numbers quantum models performed better than classical.
	For high resolution images in tests, the pretrained GAN models all suffer, but quantum still is best among method comparison.
	Also ran tests with category transfer, colorization, inpainting, and super-resolution. Quantum excelled incolorization and inpainting, was similar to classical in the other tasks
03 September 2024	**Quantum Transfer Learning for Sentiment Analysis: an experiment on an Italian corpus**
	NLP has experience tremendous recent growth thanks to deep neural networks. These are resource intensive and quantum may be an alternative
	Current NISQ hardware limits Quantum NLP to relatively easy tasks or small datasets
	Recently, a Quantum Self-Attention network has shown promise.
	This work featuers a Variational Quantum Classifier (VQC) algorithm is used with a language model to make classifcations of sentiment
	Research looks at quantum embedding where quantum concepts of superposition and entanglement are used to capture semantic relationships between words.
	Sentiment analysis is a standard NLP task where the primary emotional tone in a text is identified. Combining sentient analysis with document retrieval makes the process more intellegent and powerful.
	Sentiment analysis work with Italian language is comparitively unresearched (or underresearched?) compared to English.
	Quantum approach is unsupervised machine learning using a density matrix generated from two sentiment dictionaries

	Word relations identified in quantum are then used as inputs to a classical LSTM. High dimension word vectors are encoded into a probablistic space with a generative tensor network to classify text
	Electra is chosen as a transformer over Bert thanks to outperforming Bert on the capture of contextual word representations.
	Electra requires a large number of resoruces to train, so a pretrained Electra model was selected for the study.
	Numerical representations of sentences are encoded into quantum states using amplitude encoding. N features encoded into log(base 2) N qubits. Actual qubits used are 10 with 768 features encoded. 10 = log 1024
	Quantum states are loaded onto qubits and the run through a VQC. An optimizer finds the quantum parameters that best capture the target labels.
	Results were compiled by using a simulation with python and qiskit, not on actual hardware although quantum circuit wouldn't need to be deep based on description. No circuit diagream was provided.
	Training was run for only 8 Epochs to avoid overfitting. Training set is 4476 sentences and test set is 500 sentences. F1 score used to compare models.
	Electra with Quantum achieved better F1 score than other models. For classical comparison, Bert was compared with and without preprocessing.
	Authors do not explain why they did not use an Electra only classical baseline. There was no preprocessing for the Electra-Quantum model, perhaps the Bert preprocessing was intended to be state of the art? Unclear.
05 September 2024	**Photonic probabilistic machine learning using quantum vacuum noise**
	This is an exploration of noise generated by various computer hardware, focusing on quantum hardware
	Discusses how noise and uncertainty can be a positive in machine learning circumstances
	Use probabalistic photonic neurons for learning on MNIST dataset

	Bias noise can be tuned in this model
	It's a different angle to examine benefits of quantum computing
19 September 2024	**Buildung Continuous Quantum-Classical Bayesian Neural Networks for a Classical Clinical Dataset**
	Given NISQ limitations, compare simple quantum model to classical. Used Breast Ultrasound Imaging public data (BreastMNIST) for testing.
	Examines a hybrid Classical / Quantum approach to leverage existing quantum hardware as best as possible
	Classical CNN with quantum updating of stochastic weights, model is very simple, 2 layers, one convolutional and one fully connected
	Related work notes that there has been another hybrid quantum system designed to work with BreastMNIST dataset.
	Challenge in working with Bayesian Neural Networks is sampling the posterior distribution. Here the study uses variational inference to approximate the posterior.
	Use born machines to encode the probability distributions into quantum states. (amplitude encoding)
	Binary classifier using cross entropy created to discriminate between born machine distributions and actual distributions
	Study tried a number of different VQC methods. After trial and error, "Nikoloska" had stable results with z- rotation and x- rotation gates followed by CNOTS. z- and x- allowed full range of rotations.
	"Romero" test architecture did better than other architectures, doing it with y- rotation gates. My observation: Most NISQ don't use y- gates, all z- and x-
	Authors then created custom VQC circuits after analyzing results. Came up with four custom circuits using controlled rotation instead of CNOT gates.
	A bigger dataset would have been more useful in determining optimal VQC circuit. Many of the custom designs performed similarly.

	Classical model had better accuracy than any other model but gap may decrease with better quantum advancements
	Commendable effort went into making sure that design functioned within NISQ limitations. The VQC design was very creative, however, NISQ hardware doesn't feature all of the gates detailed in the paper.
	In other words, it was definitely simulated, however, the quantum circuit design is an excellent area to research.
19 November 2024	**The Quantum Imitation Game: Reverse Engineering of Quantum Machine Learning Models**
	If you have a given quantum model for machine learning, can you reverse engineer it to obtain potentially sensitive data? is the key issue
	Concerns are around the unitary transformations (which are reversable) composing the core of quantum computing
	Researchers believe that access to model via third party or cloud offering may reveal parameters of model
	Steps to secure models include dummy layers and increasing complexity
	Countermeasures may impact overall accuracy but can be accounted for in design
14 December 2024	**Optimizing quantum machine learning for proactive cybersecurity**
	Paper examines serveral cybersecurity datasets used in ML training to see if an advantadge is gained with the usage of quantum computing
	Solid methodology section and quantum circuit descriptions. The authors did a good job of making sure the work could be duplicated
	The ML datasets were scaled down in complexity for use with qunatum hardware
	Quantum algorithms performed nearly as well as classical algortirms in this application
	Quantum machines/circuits still have a number of limitations today such as maximum feasible qubits for features, dataset size on quantum hardware, hardware limitations such as decoherence

30 December 2024	**Hybrid quantum enhanced federated learning for cyber attack detection**
	quantum inspired federated averaging optimization part of a larger learning process to detect cyber attacks
	QIFA is claimed to use superposition and entanglement to achieve model optimization
	Paper states that quantum support vector machine is the chosen algorithm
	The quantum inspired section of the paper looks like a standard ML calculation with a noise term added to it. Definitely not qSVM
14 January 2025	**Q-SupCon: Quantum-Enhanced Supervised Contrastive Learning Architecture within the Representation Learning Framework**
	Large datasets are important for proper training of deep learning algorithms, however, some domains such as medical have privacy restrictions which make it challenging to construct a large dataset
	Curse of dimensionality' an issue where higher dimension models need more data to fight overfitting. Classical methods of dealing with limited data are being explored.
	Qunatum computing examined in hopes that the method of encoding quantum data will mitigate issues with overfitting.
	Both quantum autoencoders and quantum CNNs are sought as potential methods to address limited datasets
	Authors propose a quantum supervised contrastive learning model
	Experiment has 4 qubits for qunatum data augmentation / image processing using y-axis rotations and c-not gates. 2x2 bit blocks are selected from a larger gray scale image.
	Pixel values are encoded as angle rotations on the quantum circuit. A measurement occurs, resulting in one of two states. The c-not gate performs a bit flip if one of those two states exist.
	After the bit flip operation the value is scaled back to the 255 gray scale pixel values. This random creates more image samples to train the model.

	After the augmentation, there is an autoencoder layer. It uses a parameterized quantum circuit is used to compress the images into fewer qubits
	A swap test with new qubits is run comparing data to the autoencoded information. Measurements from this swap information become the feature vectors and are sent to classification
	Finally, a variational quantum classifier method is used on the feature vectors to determine classification.
	Two parts have to be trained, the classifier and encoder.
	In training the VQC was optimized with a gradient method and researchers had to deal with gradient dropout that is sometimes called a barren plateau. An initial guess was used with cross entropy to deal with dropout.
	Fully quantum supervised learning, tested on real quantum hardware, using trapped ion infrastructure. Was also modelled on IBM qiskit software.
	Addresses sparce data caused by privacy issues, makes training challenging
	small sample sizes (ranged 25-150) selected from MNIST, FMNIST, KMNIST datasets for training
	Test accuracy reached 80%, considerably better than classical ResNet CNN run on GPUs (ResNet had 20% accuracy)
21 January 2025	**Quantum machine learning with Adaptive Boson Sampling via post-selection**
	Paper explores the promise of photon based quantum computers which can transmit photons optically in circuits
	Big advantage is that the circuits are more robust to decoherence
	Still have challenges with designing qunatum gates for this type of hardware
	Performed SVM classification on 1-D and 2-D datasets to test hardware
29 January 2025	**Re-locative guided search optimized self-sparse attention enabled deep learning decoder for quantum error correction**
	Uses machine learning to aid in Quantum Error Correction

	Extracts features via classical CNN and outputs expected quantum states
	Proposed method is competitive with other current QEC techniques in terms of accuracy
	Authors show some possible speed up over other techniques
30 January 2025	**Superconducting quantum computing optimization based on multi-objective deep reinforcement learning**
	Method is heavily based on quantum hardware calibration for optimal performance
	Runs a qunatum state through a process with a reward term
	Deep neural network uses DQN network and Adam
	The optimization allows more complex models with more qubits
11 February 2025	**Nav-Q: quantum deep reinforcement learning for collision-free navigation of self-driving cars**
	Quantum reinforcement algorithms applied to self driving cars
	Central to self driving cars is real-time interpretation / optimization of camera data
	Clasiscal approach to this is partially observable Markov decision processes and Deep Reinforcement Learning.
	Substanial time and effort is put into designing a reinforcement learning agent.
	The idea is to have a quantum computer do the work of the reinforcement learning agent. Previous attempts have been in a simplified environment, not with real world data
	Previous works also suggest having a parameterized quantum circuit replacing or at the end of the classical deep learning model. This would require a quantum computer essentially in the car.
	There is simply no way this could work, as quantum chips are only found in large datacenters. They must be cooled to near absolute zero which is not feasible for your car.

	Model is therefore hybrid. The Quantum computing is part of the actor-critic reinforcement learning.
	The study also presents an new data uploading / encoding technique for converting classical data to quantum.
	Previous Quantum works in DRL have been assessed in OpenAI Gym environments
	Self driving background: Car has a view of objects within 50M in 360 degree range.
	Car creates a 2D map of objects using grid and birds eye view. Projects car states for 1M, 50M and 100M away. Pedestrians are also tracked.
	NavA2C is classical baseline to Quantum component. Combines path planner with modified RL agent. Agent is only responsible for speed action
	Briefly, the agent outputs the speed action, along with a reward value, the car velocity, and the previous speed action. The speed action and the steering wheel angle are passed to the self driving simulator
	DRL agent has four main components: Encoder, Actor, LSTM cell, and critic.
	For the Quantum model, the Quantum circuit is used in the critic as it is only needed for training. If a part of the algorithm was needed for testing the quantum components could not be placed in a car.
	The Quantum critic uses a paramaterize quantum circuit that takes an input of the hidden state from the LSTM cell.
	In the given example circuit, 24 classical parameters are optimized across 4 qubits.
	Output is taken from the quantum curcuir and linearly recombined as a fully connected layer.
	Simulator uses Rx, Ry, and Rz gates. May not translate into quantum hardware. Training also ran for many iterations 5000-10000 iterations
	Included a normalization layer that wasn't present in the classical RL agent.

	Study noted that the Quantum steps increased the time it took to train model. Had to decrease training from 4 qubits with 2 layers to 2 qubits with 1 layer. Also reduced LTSM state input to 6 dimensions
	Normalized Effective Dimension of Nav-Q 10x times higher than classical suggesting that more model space utilized meaning that more complex functions could be modeled.
	The experiments were run on a noise-less simulated quantum circuit. Results were promising but may not generalize well.
	When introducing noise, stability of learning dereases substantially.
	Not a clear winner in terms of performance. Classical model better at collision avoidance, hybrid model better at optimal route selection
20 February 2025	**Direct entanglement detection of quantum systems using machine learning**
	Utilizing machine learning neural network to determine entanglement of quantum system
	ML algorithm takes quantum state input and then outputs whether or not entanglement is present.
	Polynomial amount of data O(N^c) where c is a constant is needed to train model
	Method bypasses need for complex quatum full state tomography (method of pseudocopying data)