Quantum Machine Learning for Optical and SAR Classification

Leslie Miller, Glen Uehara, Aradhita Sharma, Andreas Spanias
SenSIP Center, School of ECEE
Arizona State University
Tempe, AZ 85287-5706, USA

***Abstract*—We present in this paper a method to compare scene classification accuracy of C-band Synthetic aperture radar (SAR) and optical images utilizing both classical and quantum computing algorithms. This REU study uses data from the Sentinel satellite. The dataset contains (i) synthetic aperture radar images collected from the Sentinel-1 satellite and (ii) optical images for the same area as the SAR images collected from the Sentinel-2 satellite. We examine classical neural networks to classify four classes of images. We then explore Quantum Convolutional Neural Networks and deep learning techniques in terms of their training and classification performance. A hybrid Quantum-classical model that is trained on the Sentinel1-2 dataset is proposed, and its performance is then compared against the classical model in terms of classification accuracy.**

Keywords— SAR, radar, REU, Neural Networks, VGG16, deep learning, Quantum convolutional neural network.

I. Introduction

The need for workforce development in quantum information science was emphasized in several quantum computing initiatives and presidential committee announcements. In this NSF Research Experience for Undergraduates (REU) research and education project, an undergraduate Electrical Engineering student at Arizona State University (ASU) was immersed in quantum machine learning (QML) studies for SAR and Optical scene classification. Scene classification, using deep learning techniques is having a great impact in the field of remote sensing [1]. This REU effort addresses some of the challenges surrounding SAR datasets and explores feature extraction and QML [2]. Students and their mentors began this REU study in 2022 by participating in "bootcamp" training in digital signal processing, machine learning (ML) basics, and quantum computing. Lecture topics included basics on fast Fourier transforms, quantum Fourier transforms, image processing, denoising techniques, and fundamentals of machine learning [3]. Simple ML concepts and algorithms were introduced using J-DSP [4], MATLAB, and Python. The REU student was co-mentored by a PhD student and the ASU faculty PI of the REU. In addition, the REU student participated in weekly research update sessions where she presented weekly progress. Our REU efforts and the process we use to recruit, train and embed undergraduate students in research are described in [5,6]. Recent and past statistics on our REU program are given in evaluation reports [7].

The topic of scene classification from satellite images was chosen because of challenging surveillance applications that are important to some of our industry and government sponsors. Imaging applications include navigation, space exploration, iceberg and weather tracking, and surveying the effects of global warming [8]. Challenges in using ML for image classification include a) finding a labeled dataset with optical and corresponding SAR images b) denoising the SAR images c) selecting an appropriate ML algorithm and d) designing QML simulation circuits for optical and SAR datasets. In our study, datasets from the Sentinel satellites are used. The Sentinel satellites are a part of the Copernicus space program of the European Space Agency (ESA) [1]. One of the main goals of this program is to ensure data continuity for applications in ocean, atmosphere, and land monitoring [1]. Six different satellite missions are encompassed in this program. All six missions are focused on ensuring data integrity for land monitoring. In our study, we focus on images from two satellites, namely, Sentinel-1 and Sentinel-2. Both satellites provide reliable conventional remote sensing images obtained by synthetic aperture radar and optical sensors [1].

The SEN1-2 dataset consists of 282,384 pairs of corresponding image patches. These images are collected across the globe and include various meteorological seasons, including summer and fall. More details of the SEN1-2 dataset can be seen in the database section of this paper. Given the complex nature of the Sentinel1-2 dataset, there is a need for new techniques to extract spectral details from the images.

In this paper, we describe the classical and quantum ML approaches to classify images from the Sentinel 1-2 dataset. One of the main REU project objectives is to use QML approaches for image classification and compare them against classical ML. The quantum classification approach here uses hybrid quantum neural network (QNN) architectures such as the one shown in Figure 1.

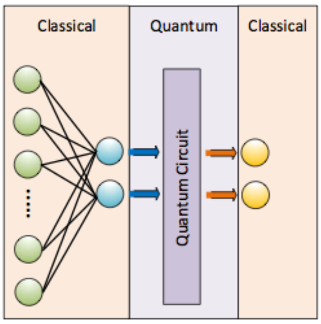

Fig. 1. Hybrid Quantum Neural Network Architecture [2].

979-8-3503-3959-8/23/$31.00 ©2023 IEEE

QNNs have been used in various imaging, audio, and other classification applications [9,10]. Our classification databases include four categories of images, namely: Agriculture, Grassland, Barren land, and Urban. For classical neural network architecture, we decided to explore the visual geometric group VGG-16 [9,11] classifier.

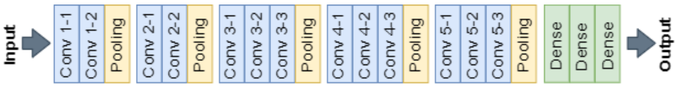

Fig. 2. The VGG16 Architecture [9].

Initially, we trained a classical convolutional neural network (CNN) on our dataset. We obtained low accuracy, and we concluded that this initial CNN model was not well suited for our dataset. We then began examining a VGG-16 model. This improved our classification accuracy to 85.04%. The VGG16 architecture can be seen in Figure 2 [9]. Once classical classification was performed, we trained the dataset using a "quanvolutional" neural network.

The rest of the paper is organized as follows. Section II presents a brief literature review. In Section III, we describe the architecture adopted, the pre-processing stage, and feature extraction strategies for classical methods. In Section IV, we describe quantum machine learning approaches and quantum simulation circuit designs. We report our results in Section V. In Section VI, we provide concluding remarks.

II. Literature Review

A. *Classical SAR Image Analysis*

Synthetic Aperture Radar (SAR) is a microwave remote sensing method. The use of SAR and optical images for edge detection and image classification has found several applications through the years. It uses impulse compression which increases the resolution distance and provides a two-dimensional map of the radar reflectivity of the scene. SAR images can be hard to process due to speckle noise, making it difficult to decipher the edges in the image [8]. Two essential steps in processing SAR images are edge detection and feature extraction. Wang et al. proposed a dual-stage coupled CNN architecture (DCC-CNN) to classify multiple categories of SAR images. The DCC-CCN method consists of two parts. This includes a despeckling subnetwork and a classification network. The average classification result for the DCC-CNNs method was 82.19% [12]. Another classical method for SAR images was described by Falqueto et al. where they used VGG-16 (16 layers) and VGG-19 (19 layers) architectures and obtained an accuracy of 86.4% and 84.1%, respectively [10].

B. *Optical Images – Classical Computing*

Optical images have similarities with the way humans perceive their surroundings. Therefore, optical images are easier to understand and process [13]. Most deep-learning models are optimized for optical images [14]. Cheng et al. performed scene classification using three CNN models, including AlexNet, VGGNet, and GoogleNet, and the classification accuracy of 98.33% using GoogleNet, 98.10% using VGGNet, and 97.14% using the AlexNet [11].

C. *Quantum Approaches*

One of the reasons quantum machine learning is of interest is its ability to process large amounts of data faster than classical techniques. QML uses a quantum computer's increased computing power to integrate into a machine learning model [9]. One method of implementing QML is replacing a classical layer with a quantum layer [9]. In this method, the input data to the layer are encoded in qubits which result in the quantum representation of the input data, which is processed by the quantum layer. The qubits are measured and then converted back into classical values to be mapped to pixel output and are then passed on to the next layer [10]. Chen et al. described three different quantum techniques for scene classifications including a QCNN, Hybrid QCNN, and a Hybrid QCNN with multiple quantum layers. These three techniques achieved accuracies from 83%-88%, whereas the classical CNN achieved an accuracy of about 82%-84% [15].

D. *The Sentinel Databases*

The Sentinel-1 mission has two polar-orbiting satellites. These satellites are equipped with C-band SAR sensors [1]. C-Band SAR operates at a frequency of 4-8 GHz and is the "SAR Workhorse" [16,17]. Typical applications for C-Band include global mapping, change detection, monitoring areas with low to moderate penetration, ocean maritime navigation, and changes to arctic ice [16]. SAR is a powerful imaging technique that can see through all-weather types and is independent of daylight conditions [17,18].

The Sentinel-2 mission consists of twin polar orbiting satellites in the same orbit [16]. They are phased at 180 degrees to each other. The images captured from Sentinel-2 are optical images and only use the red, blue, and green channels. To capture images that are useful in image processing, acquisition needs to be done in cloud-free conditions.

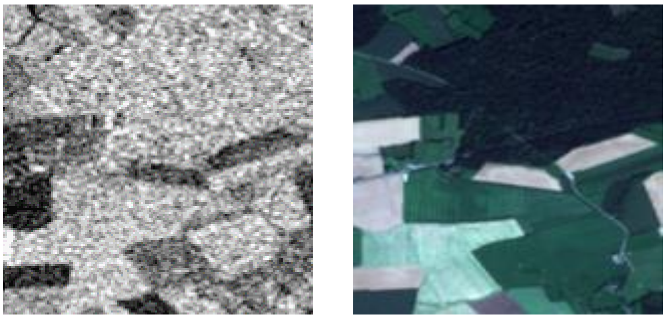
Fig. 3. Paired Images from SEN12 Dataset [1].

Figure 3 gives an example of an optical image from the agriculture class, with the corresponding SAR image [1].

III. Classical Scene Classification

We performed classical scene classification on both the SAR and Optical Image Datasets. For the optical classical scene classification, the VGG16 and the Recurrent Neural Network (RNN) were used. The images were resized to 64x64 pixels and separated into 4 classes: agriculture, barren land, grassland, and urban. A flattened version of this image was then used to form training and testing vectors for the neural network [14]. We began our study using Convolutional Neural networks and ResNet; however, we did not obtain satisfactory accuracy [19]. We also began testing other ML algorithms and found that the VGG16 and RNN performed the best [20]. The Visual Geometry Group 16 (VGG16) is a standard deep convolutional neural network consisting of multiple layers. The VGG16 consists of thirteen convolutional layers and three fully connected layers [9, 21]. It is one of the most popular image recognition architectures. Using this approach, we obtained a confusion matrix showing an initial classification accuracy of 85.04% for the optical image dataset. The confusion matrix obtained for the classical VGG16 can be seen in Figure 4.

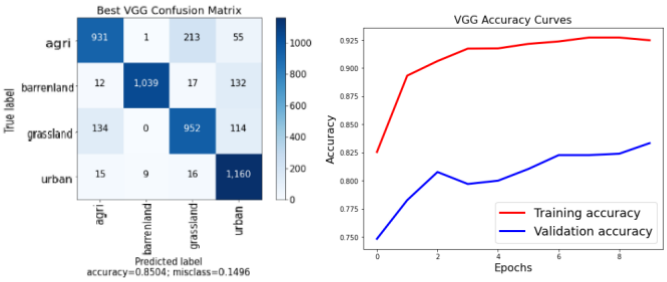

Fig. 4. Confusion Matrix and Accuracy Curve for VGG16 - Optical Image Dataset.

We initially ran the large SAR image dataset through the VGG16. Using this approach, we obtained a confusion matrix showing an initial accuracy of 77.19%. We decided to try another approach, using an RNN on the smaller dataset. The RNN gave a training accuracy of approximately 69.53%. More results are detailed in Table 1 and Table 2.

IV. Quantum Scene Classification

A. Challenges, Dataset, and Preprocessing

There were a few challenges encountered when using a quantum model. We experienced very long run times when particularly training the algorithms. In addition to long run times, our quantum model struggled in the classification of the entire dataset. Therefore, we used a smaller dataset in addition to the full dataset. Quantum processing also requires careful pre-processing in order to extract features from the data [22].

B. Quantum Circuit and Feature Extraction

We explored several software tools for the design and construction of quantum circuits as well as the simulation of their behavior. IBM's Qiskit can be utilized to program and simulate the quantum circuits, while the implementation of QML can be facilitated with the use of Qiskit and Keras frameworks [23, 24]. We also examined the use of the quantum Fourier transform in signal analysis [28,29].

To perform feature extraction, we used a four-qubit quantum circuit [22, 25, 26]. This circuit can be seen in Figure 5. The circuit includes an RY gate and then Unitary gates. The Unitary gates are a set of gates that can perform roation through continuously changing weights [22, 25]. We ran randomized gates on each of the qubits to find which random circuit works the best [22, 27]. In our neural network design, we add a quantum neural layer at the beginning to determine if encoded features can be extracted from the images. In our example, the neural layer depends on encoding initialization, quantum circuit parameters, and decoding measurement [21, 25]. The neural network architecture with a quantum neural layer can be seen in Figure 6.

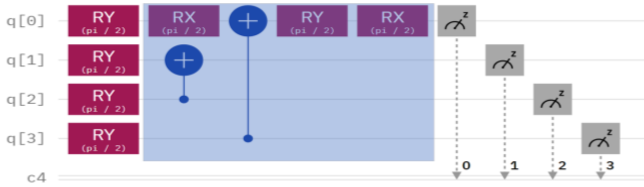

Fig. 5. A 4-Qubit Quantum Circuit for Image Classification.

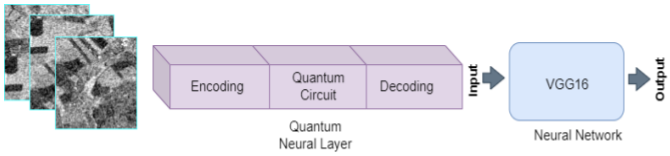

Fig. 6. Neural Network Architecture with Quantum Neural Layer.

C. Neural Network Models and Training

A Quantum-classical hybrid architecture is evaluated in this REU research. Quantum convolutional layers ("quanvolutional") are combined with a classical neural network model for the classification of SAR and optical images into four classes. Benefits for a quanvolutional neural network include dramatically reduced training time and reduced memory requirements [22, 26]. Other studies that used QNNs for various applications include [30-37].

We used an RNN and a VGG16 in our quanvolutional model. Both neural networks were trained using an 80/20 train/test split and were trained for 10 epochs. The Keras machine learning package was used in Python for the implementation of our algorithm [24]. Due to the larger dataset struggling to be processed on a quantum simulator, we used a smaller dataset to test our algorithm with the SAR images. The hybrid classical quantum model for SAR scene classification can be seen in Table I and Table II.

Although the classification accuracy was less than the classical ML algorithm, with more data the Quantum convolution model converges faster, using fewer epochs. This can be seen in Figure 7 and Figure 8.

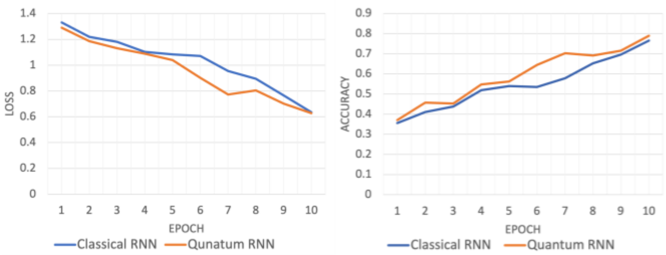

Fig. 7. RNN Loss and Accuracy Results of Classical (blue) and Quantum (red) with increased number of data points.

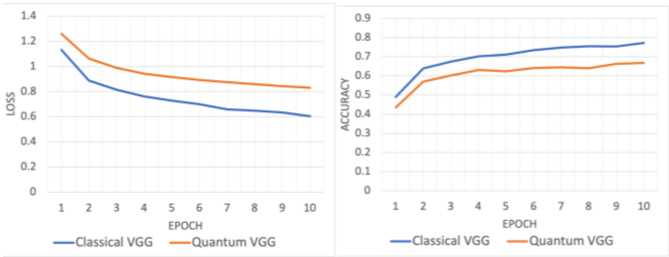

Fig. 8. VGG16 Loss and Accuracy Results of Classical (blue) and Quantum (red) with increased number of data points.

V. Discussion of Results

A. *Classical and Quantum VGG results for a large dataset*

We first ran the full SAR image dataset through a classical VGG16 and a VGG + Quanvolutional Neural Network. The full dataset size consisted of 16,000 images. The classical VGG16 network had a training accuracy of about ~77%. We then ran the images through a VGG16 and a *quanvolutional* neural network, which gave a training accuracy of 66.72%. The rest of the results can be seen in Table I.

TABLE I. Testing with VGG for Large SAR Dataset

Neural Network Model	**Data Size (train vs validation)**	**Accuracy (train vs validation vs test)**	**Parameters**
VGG	train: 1280 validation: 320	train: 0.7719 validation: 0.7250 test : 0.7250	Total params: 14,722,884 Trainable params: 8,196 Non-trainable params: 14,714,688
VGG	train: 1280 validation: 320	train: 0.7547 validation: 0.7250 test : 0.7250	Total params: 14,722,884 Trainable params: 8,196 Non-trainable params: 14,714,688
VGG + Quanvolution	train: 1280 validation: 320	train: 0.6414 validation: 0.5938 test : 0.5938	Quantum: 4 - Qubits Classical: Total params: 14,722,884 Trainable params: 8,196 Non-trainable params: 14,714,688
VGG + Quanvolution	train: 1280 validation: 320	train: 0.6672 validation: 0.5938 test : 0.5094	Quantum: 4 - Qubits Classical: Total params: 14,722,884 Trainable params: 8,196 Non-trainable params: 14,714,688

B. *Classical and Quantum RNN results for a small dataset.*

The SAR dataset is harder to process both with classical and quantum computing. We used an RNN on a smaller set of SAR images to examine if we would get better results for the SAR and quantum data. However, the results did not show great improvement. The results for the SAR data can be seen in Table II.

VI. Conclusion

This REU program provided advanced training in python programming, machine learning, DSP, and quantum machine learning. These skills were applied to produce the results in Optical and SAR scene classification. Classical and quantum algorithms were examined for both the SAR dataset and the optical dataset. Our simulations revealed that best results were obtained with the VGG16. In fact, the VGG16 performed better than the RNN for the SAR images; however, further validation and improvement is needed. The initial quantum simulations for both the optical and SAR datasets were below 60% which is not satisfactory at this point. Low QNN performance was attributed to quantum noise effects, low qubit precision, and limited training of the QNN architecture. We emphasize that the training of the QNN in this REU study was also limited by exceedingly lengthy computation times and limited access to GPU arrays. Nevertheless, the REU study was innovative and impactful in that it provided a unique opportunity for the undergraduate student to receive advanced algorithmic, VGG, QNN, and programming experiences in a challenging field. Future work includes more elaborate training and optimization of the QML algorithms. In addition to using techniques proposed in this paper, we are exploring the use of methods such as image fusion and the use of a quantum filter, to achieve higher accuracy.

TABLE II. Testing with RNN for Smaller SAR Dataset

Neural Network Model	**Data Size (train vs validation)**	**Accuracy (train vs validation vs test)**	**Parameters**
RNN	train: 256 validation: 64	train: 0.6953 validation: 0.5000 test : 0.3125	Total params: 181,317 Trainable params: 181,181 Non-trainable params: 136
RNN	train: 256 validation: 64	train: 0.7656 validation: 0.3750 test : 0.5938	Total params: 181,317 Trainable params: 181,181 Non-trainable params: 136
RNN + Quanvolution	train: 256 validation: 64	train: 0.7148 validation: 0.4531 test : 0.3906	Quantum: 4 - Qubits Classical: Total params: 181,317 Trainable params: 181,181 Non-trainable params: 136
RNN + Quanvolution	train: 256 validation: 64	train: 0.7891 validation: 0.3906 test : 0.3906	Quantum: 4 - Qubits Classical: Total params: 181,317 Trainable params: 181,181 Non-trainable params: 136

Acknowledgement

Portions of this study have been supported by the SenSIP Center, the ASU KE Quantum Collaborative and the NSF awards 1540040, 1659871, 1854273, and 2215998.

REFERENCES

[1] M. Schmitt, L. H. Hughes, and X. X. Zhu, “The SEN1-2 dataset for deep learning in SAR-optical data fusion,” *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. IV-1, pp. 141–146, 2018.

[2] G. Uehara, A. Spanias, W. Clark, “Quantum Information Processing Algorithms with Emphasis on Machine Learning,” *Proc. IEEE IISA 2021*, July 2021.

[3] A. Spanias, “Digital Signal Processing: An Interactive Approach,” Second ed., Lulu Publishing, 2014.

[4] A. Dixit and U. Shanthamallu, A. Spanias, V. Berisha, M. Banavar, Online Machine Learning Experiments in HTML5, *IEEE FIE 2018*, San Jose, October 2018.

[5] A. Spanias and J. Blain Christen, “A STEM REU Site On The Integrated Design of Sensor Devices and Signal Processing Algorithms,” *Proc. IEEE ICASSP 2018*, Calgary, April 2018.

[6] ASU SenSIP REU Program https://sensip.engineering.asu.edu/reu-index-html/

[7] W. Barnard, NSF REU Evaluation Reports, Program NSF 1659871, ASU CREST reports 2017-2022.

[8] Wang Min and Yuan Shuyuan, "A hybrid genetic algorithm-based edge detection method for SAR image," *IEEE International Radar Conference,* pp. 503-506, Arlington, VA, USA, 2005.

[9] G. Learning, “Everything you need to know about VGG16,” Medium, 23-Sep-2021]. https://medium.com/@mygreatlearning/everything- you-need-to-know-about-vgg16-7315defb5918.

[10] L. E. Falqueto, J. A. S. Sá, R. L. Paes and A. Passaro, "Oil Rig Recognition Using Convolutional Neural Network on Sentinel-1 SAR Images," in *IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 8, pp. 1329-1333, Aug. 2019.

[11] G. Cheng, C. Ma, P. Zhou, X. Yao and J. Han, "Scene classification of high resolution remote sensing images using convolutional neural networks," *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* Beijing, China, 2016, pp. 767-770.

[12] J. Wang, T. Zheng, P. Lei and X. Bai, "Ground Target Classification in Noisy SAR Images Using Convolutional Neural Networks," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 11, pp. 4180-4192, Nov. 2018.

[13] Admin, “Lidar and Radar Information,” – LiDAR and RADAR Information. [Online]. Available: https://lidarradar.com/info/optical-imagery-vs-radar-sensing-is-one-better.

[14] S. R. Majji, A. Chalumuri, R. Kune and B. S. Manoj, "Quantum Processing in Fusion of SAR and Optical Images for Deep Learning: A Data-Centric Approach," in *IEEE Access*, vol. 10, pp. 73743-73757, 2022.

[15] G. Chen, Q. Chen, S. Long, W. Zhu, Z. Yuan, and Y. Wu, “Quantum convolutional neural network for Image Classification,” *Pattern Analysis and Applications, 2022.*

[16] N. Arslan, “Assessment of oil spills using Sentinel 1 C-band SAR and Landsat 8 multispectral sensors,” *Environmental Monitoring and Assessment,* vol. 190, no. 11, 2018.

[17] NASA Earth Science Data Systems, “What is Synthetic Aperture Radar?” NASA, 10-Apr-2020. [Online]. Available: https://www.earthdata.nasa.gov/learn/backgrounders/what-is-sar.

[18] T. P. Ager, The essentials of SAR: A conceptual view of synthetic aperture radar and its remarkable capabilities. Delaware: Thomas P. Ager, 2022.

[19] G. Boesch, “Deep residual networks (ResNet, RESNET50) - 2023 guide,” viso.ai, 02-Jan-2023. [Online]. Available: https://viso.ai/deep-learning/resnet-residual-neural-network/.

[20] B. Chandra and R. K. Sharma, "On improving recurrent neural network for image classification," *2017 International Joint Conference on Neural Networks (IJCNN),* Anchorage, AK, USA, 2017, pp. 1904-1907.

[21] N. L. Tun, A. Gavrilov, N. M. Tun, D. M. Trieu and H. Aung, "Remote Sensing Data Classification Using A Hybrid Pre-Trained VGG16 CNN-SVM Classifier," *2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus),* St. Petersburg, Moscow, Russia, 2021, pp. 2171-2175.

[22] M. Esposito, G. Uehara and A. Spanias, "Quantum Machine Learning for Audio Classification with Applications to Healthcare," *2022 IEEE 13th International Conference on Information, Intelligence, Systems & Applications (IISA),* Corfu, Greece, 2022, pp. 1-4.

[23] W. Jiang, J. Xiong and Y. Shi, "When Machine Learning Meets Quantum Computers: A Case Study," *2021 26th Asia and South Pacific Design Automation Conference (ASP-DAC),* Tokyo, Japan, 2021, pp. 593-598.

[24] “Simple. flexible. powerful.,” Keras. [Online]. Available: https://keras.io/.

[25] P. Foy, “Introduction to quantum programming with Qiskit,” MLQ.ai, 12-Dec-2022. [Online]. Available: https://www.mlq.ai/quantum-programming-with-qiskit/.

[26] M. Esposito, S. Rao, V. Narayanaswamy and A. Spanias, "COVID-19 Detection using Audio Spectral Features and Machine Learning," *2021 IEEE 55th Asilomar Conference on Signals, Systems, and Computers,* Pacific Grove, CA, USA, 2021, pp. 1146-1150.

[27] Bouland, et al. On the complexity and verification of quantum random circuit sampling. *Nature Phys* 15, 159–163 (2019).

[28] A. Sharma, G. Uehara, V. Narayanaswamy, L. Miller and A. Spanias, “Signal Analysis-Synthesis using the quantum Fourier Transform.” *2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).* IEEE, Rhodes, 2023.

[29] Peter W. Shor "Polynomial-time algorithms for prime factorization and discrete logarithms on a quantum computer." *SIAM review* 41.2 (1999): 303-332.

[30] G. Uehara, S. Rao, M. Dobson, C. Tepedelenlioglu and A. Spanias, "Quantum Neural Network Parameter Estimation for Photovoltaic Fault,” *Proc. IEEE IISA 2021,* July 2021.

[31] G. Uehara, J. Larson, W. Barnard, M. Esposito, F. Posta, M. Yarter, A. Sharma, N. Kyriacou, M. Dobson, A. Spanias, "Undergraduate Research and Education in Quantum Machine Learning,” *IEEE FIE 2022,* Upsala, Oct. 2022

[32] Kwak, Yunseok, Won Joon Yun, Soyi Jung, and Joongheon Kim. "Quantum neural networks: Concepts, applications, and challenges." *2021 Twelfth International Conference on Ubiquitous and Future Networks (ICUFN),* pp. 413-416. IEEE, 2021.

[33] M. Yarter, G. Uehara, A. Spanias, “EDGE Cloud Voice Recognition Using Quantum Neural Networks,” *IEEE MWCAS 2023*, Tempe, August 2023. (submitted)

[34] G. Uehara, V. Narayanaswamy, C. Tepedelenlioglu, A. Spanias, “Quantum Machine Learning for Photovoltaic Topology Optimization,” *2022 IEEE 13th IISA, Hybrid Conference*, July 2022.

[35] V. Gandhi, G. Prasad, D. Coyle, L. Behera and T. M. McGinnity, "Quantum Neural Network-Based EEG Filtering for a Brain–Computer Interface," *in IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 2, pp. 278-288, Feb. 2014.

[36] S. Chakraborty, T. Das, S. Sutradhar, M. Das and S. Deb, "An Analytical Review of Quantum Neural Network Models and Relevant Research," *2020 5th International Conference on Communication and Electronics Systems (ICCES),* Coimbatore, India, 2020, pp. 1395-1400.

[37] A. Sebastianelli, D. A. Zaidenberg, D. Spiller, B. L. Saux and S. L. Ullo, "On Circuit-Based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification," *in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 565-580, 2022.