Best Student Paper Award

Quantum Classification for Synthetic Aperture Radar

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ABSTRACT

The field of quantum computing, especially quantum machine learning (QML), has been the subject of much research in recent years. Leveraging the quantum properties of superposition and entanglement promises exponential decrease in computation costs. With the promises of increased speed and accuracy in the quantum paradigm, many classical machine learning algorithms have been adapted to run on quantum computers, typically using a quantum-classical hybrid model. While some work has been done to compare classical and quantum classification algorithms in the Electro-Optical (EO) image domain, this paper will compare the performance of classical and quantum-hybrid classification algorithms in their applications on Synthetic Aperture Radar (SAR) data using the MSTAR dataset. We find that there is no significant difference in classification performance when training with quantum algorithms in ideal simulators as compared to their classical counterparts. However, the true performance benefits will become more apparent as the hardware matures.

Keywords: Quantum Machine Learning, Quantum, Classification, Machine Learning, Synthetic Aperture Radar, SAR

1. INTRODUCTION

In the rapidly evolving field of remote sensing, Synthetic Aperture Radar (SAR) data stands out for its ability to provide high-resolution images in any weather condition and irrespective of daylight availability. This capability makes SAR data indispensable for a wide range of applications, from environmental monitoring to military surveillance. By comparing quantum-hybrid machine learning with traditional approaches, this paper aims to explore how the unique advantages of quantum computing, such as parallelism and entanglement, could lead to more efficient algorithms. This comparison not only highlights the potential for advancements in SAR data analysis but also paves the way for a new era in remote sensing technology, where quantum-enhanced algorithms could offer solutions to some of the most challenging problems in the field. If we can achieve similar accuracy with the quantum algorithm, then this could translate to significant speed-up of the algorithm in the future when quantum hardware is more readily available.

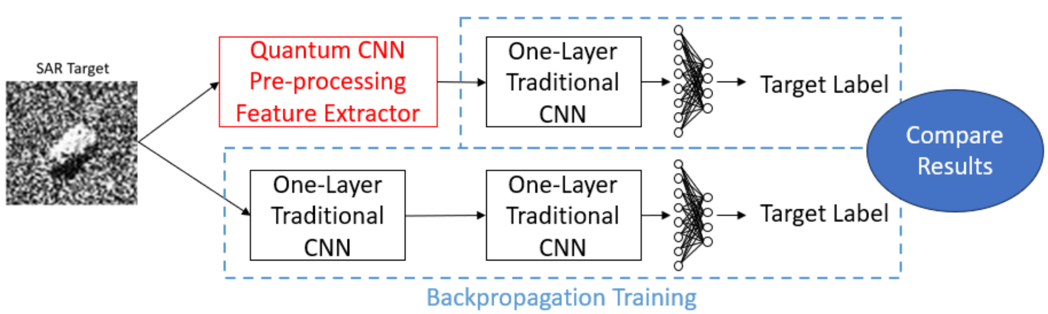

Figure 1: High level figure on the “marriage” of SAR and hybrid QNN.

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In this section, we briefly describe SAR imaging, how it differs from optical imaging, and why it is a valuable tool in remote sensing applications. We then introduce quantum machine learning (QML), its quantum-classical hybrid form, current research in the field, and our purposes for using it in this research. We conclude this introduction with a description of our contributions to the field and the organization of the rest of the paper.

1.1 Synthetic Aperture Radar (SAR)

Synthetic Aperture Radar (SAR) is a type of remote sensing radar technology used to create high-resolution coherent imagery regardless of weather conditions or time of day. In addition, SAR offers further advantages over traditional Electric-Optical (EO) imaging such as weather/shadow invariance and range independent resolution. This allows SAR imagery to be used when EO imaging cannot. Unlike traditional radar systems that rely on physical antenna size for resolution, SAR uses the movement of the radar antenna over a target area to simulate a much larger antenna or aperture synthetically. This process enables SAR to produce finely detailed images with much higher resolution than standard radar.

While incredibly useful in remote sensing, SAR imagery is not always easily interpretable by humans and often requires expert level human annotation to interpret. Training for this level of annotation can take years. Because of this, there is a massive need for automated techniques of SAR scene and image classification - AI and machine learning techniques are a natural fit. At the same time, in addition to being more difficult for a human, SAR is also more difficult than EO imagery for current machine learning algorithms to learn. SAR data represents radar backscatter instead of visible light reflection. This results in high levels of speckle noise which is intrinsic to the coherent nature of the radar imaging process but complicates the learning process. Many EO machine learning algorithms are dependent on edge detection in images to assist classification. The heavily speckled nature of SAR limits the usefulness of edge detection for feature extraction.

Early work in SAR classification used SVMs and other classical machine learning approaches [1]. Deep learning techniques such CNNs (convolutional neural nets), autoencoders, and transfer learning are commonly used for SAR classification tasks today [2]. In 2014, [3] found that a simple feature extraction using a pre-processing single-layer CNN could be used to improve SAR classification on the MSTAR dataset. Deeper CNNs were investigated in [4], and metric learning was added to improve performance in [5]. In recent years, transfer learning has become a common approach, enabling better learning with fewer labeled data. [6] illustrates the effectiveness of transfer learning with deep CNNs for SAR target classification, emphasizing CNNs' capability to learn hierarchical image features essential for SAR classification tasks. Unsupervised representation learning [7][8] can be used with transfer learning to improve overall performance.

For further information on SAR technology, [9] presents a great tutorial on the subject.

1.2 Quantum Machine Learning (QML)

Quantum Machine Learning (QML) uses the capabilities of quantum computing to process and analyze data in ways that are fundamentally different from traditional machine learning. By leveraging quantum bits (qubits), which can exist in multiple states simultaneously via superposition, and can influence one another instantaneously through entanglement, QML algorithms can theoretically perform complex calculations at a speed and efficiency unattainable by classical algorithms [10][11][12][13]. This makes QML particularly useful for handling vast datasets and executing tasks like pattern recognition, optimization, and classification with unprecedented speed [14][15]. Due to current technical limitations including high quantum noise, extensive error correction techniques, and limited availability of real quantum computers, most published QML research today is conducted on quantum computer simulations.

There are different ways this can be done. Quantum circuit learning introduces a hybrid classical-quantum algorithm for machine learning on near-term quantum processors [16]. Quantum Boltzmann machines, inspired by classical Boltzmann machines, use a novel machine learning approach based on the quantum Boltzmann distribution [17]. Quantum convolutional neural networks (QCNNs), a type of QML analogous to Convolutional Neural Networks (CNNs) for image classification, have been developed to address highly complex quantum problems that are difficult to solve using current classical and quantum machine learning techniques [18][19][20][21][22]. QCNNs are structured similarly to classical CNNs but using quantum circuits to perform the convolutional and pooling operations. These quantum circuits manipulate qubits in ways that classical bits cannot be manipulated, enabling the quantum network to capture correlations in data that might be too complex for classical neural networks. Most existing research has used these QCNNs for optical image classification purposes.

1.3 QML for SAR

Very little work has been done using QML with SAR. Most QML in remote sensing has been on standard EO images. Recent work, [23][24], using QML for EO-SAR Fusion has demonstrated high performance with a reduction in complexity and memory requirements using the low-resolution Sentinel-1 and 2, datasets. In this paper, we perform the first step in QML target classification on the higher resolution SAR MSTAR dataset. Applying QML to SAR target classification is a new problem and has not been done before to the best of our knowledge. As with most of the papers referenced in the sections above, we use a quantum simulator rather than true quantum hardware. This is described in more detail in section 2.

1.4 Contributions to the field and paper organization

This paper provides an initial look at using quantum-hybrid classification techniques on SAR target imagery. The purpose of this research is to identify whether quantum computing might have potential for SAR applications in the future. This work differs from previous studies [23][24] and contributes to the field of remote sensing by applying these hybrid techniques on automatic target recognition (ATR) using the MSTAR dataset. While these previous papers explored quantum fusion with C-band SAR and optical images for scene classification, this study will focus on target classification using high resolution X-band SAR images.

This paper is organized as follows. In section 2, we describe the experimental setup in more detail, including the traditional and quantum machine learning algorithms and the dataset.
In section 3 we provide results and proceed to future work and conclusions in sections 4 and 5 respectively.

2. EXPERIMENTAL SETUP

The experimental setup is broken into three parts. First, we describe the machine learning classification setup in section 2.1, then a close description of the quantum details in section 2.2, and finally a description of the SAR dataset used in this research in section 2.3.

2.1 Machine Learning Models

Two separate machine learning models were used in this research - a classical CNN and a simulated and idealized quantum-hybrid CNN with a random quantum circuit. The structure of these models was kept extremely similar to allow for comparison between model types. They both contained two convolutional layers, the first of which was replaced by a quantum convolution in the hybrid algorithm, as shown in Figure 2 below. Due to the long runtimes of quantum simulations, the hybrid model was run five times to obtain average results while the classical model was run 20 times.

The CNNs investigated in this study consisted of two convolutional blocks containing a convolution and max pooling layer. This was followed by a fully connected classification head with two hidden layers consisting of 30,752 and 128 neurons, in the hybrid algorithm, and 28,800 and 128 neurons in the classical algorithm. Input images were reshaped to be 128x128 pixels and a dropout rate of 0.25 was employed between each fully connected layer and the final convolutional layer. The hybrid model implements the first convolutional block with quantum algorithms while the classical model did not. The hybrid model also omits the activation function and max pooling layer on the first convolutional block. The lack of an efficient quantum back propagation algorithm restricts the hybrid model from providing weight updates to its quantum kernels, meaning that these weights remain fixed during training. For a full description of the model architectures, refer to appendices A and B.

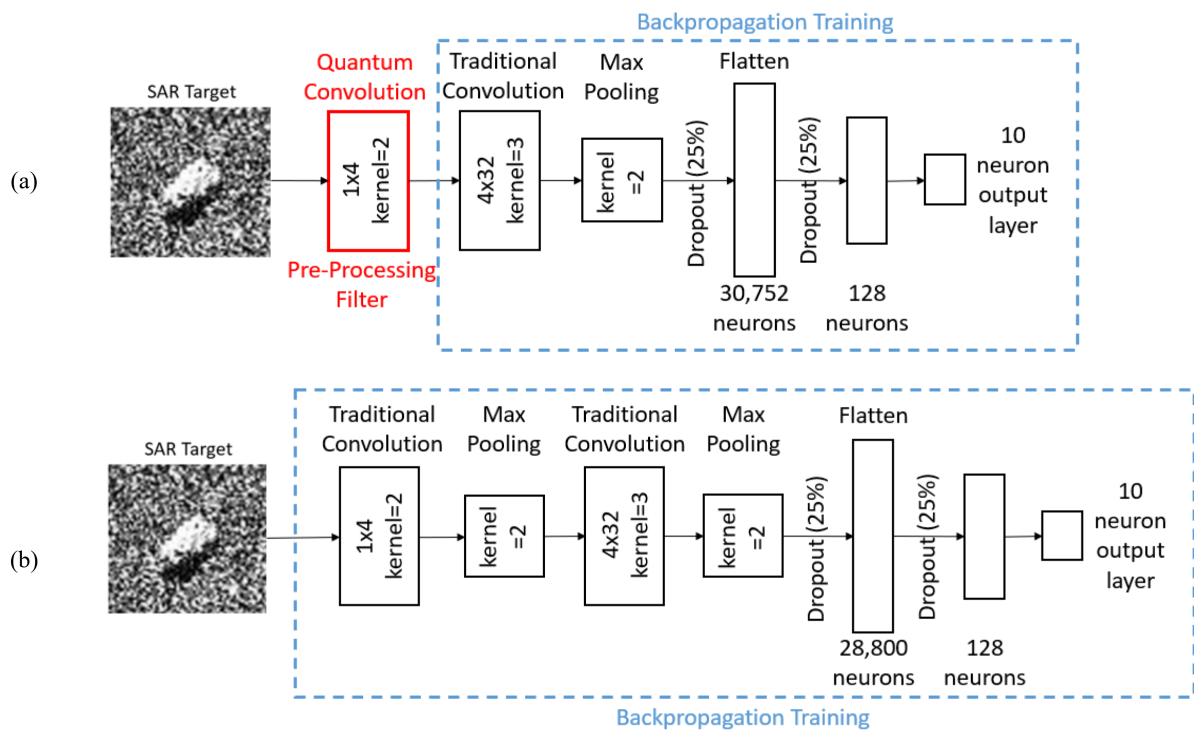


Figure 2. Comparison between the hybrid (a) and classical (b) models used in this experiment.

2.2 Hybrid Quantum CNN

The hybrid model employs a quantum convolution layer, having a kernel size of 2x2 and a stride of 2. Each pixel of the kernel is first encoded into a quantum state and then run through a randomly generated 4-qubit quantum circuit using the Pennylane quantum simulator [25]. This follows the ideas proposed in [18], where a quantum convolution with a random quantum circuit yielded promising results in MNIST image classification. By using Pennylane's RandomLayers function, we constructed these random quantum circuits out of two-qubit entangling gates and single-qubit rotation gates with random rotation parameters (Figure 3). Details about the gates used in these circuits can be found in Table 1 below.

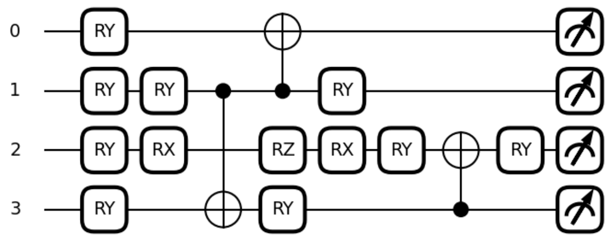
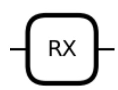
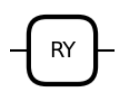
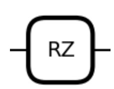
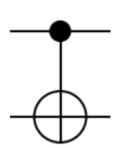


Figure 3. One of the five randomly generated quantum circuits used in this study.

While there are many methods of encoding classical information into a quantum circuit, the format chosen for this study encodes each pixel in the kernel into a separate qubit by scaling the rotation in RY gates from 0 to π based on the pixel value. This common method of "angle encoding" maintains the simplicity of the circuit while ensuring a high-fidelity input. The qubits are then measured by retrieving the expected values of the Pauli Z observable on each qubit. Each of these four measured values, which scale from 0 to 1, are then appended to a separate channel of the output. Therefore, the outputs of the quantum convolution are four 64x64 feature maps.

All the quantum simulations in this study were conducted assuming an "ideal" environment with no noise. However, if the effects of quantum noise are factored into the simulations, related work suggests that a roughly 2% degradation of accuracy is expected [24].

Table 1. Quantum gates used in this study.

Gate	Representation	Matrix
Rx(θ)		$\begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -i\sin\left(\frac{\theta}{2}\right) \\ -i\,sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$
Ry(θ)		$\begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -\sin\left(\frac{\theta}{2}\right) \\ sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$
Rz(θ)		$\begin{pmatrix} e^{-i\frac{\theta}{2}} & 0 \\ 0 & e^{i\frac{\theta}{2}} \end{pmatrix}$
CNOT		$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$

2.3 MSTAR Dataset

In this paper, we use the publicly available MSTAR dataset [26], short for Moving and Stationary Target Acquisition and Recognition. MSTAR is a widely used benchmark dataset in the field of synthetic aperture radar (SAR) image analysis. Developed by the U.S. government's Defense Advanced Research Projects Agency (DARPA), MSTAR provides researchers and developers with a comprehensive collection of SAR images for target detection, recognition, and classification tasks. It serves as a useful resource for evaluating and advancing algorithms and techniques in SAR image processing and target recognition.

MSTAR consists of approximately 5000 high-resolution images of the 10 different SAR targets shown in Figure 4 below. These targets have been imaged at full 360-degree aspect coverage. The training set consists of 2747 images, collected at a depression angle of 15 degrees, while the testing set consists of 2425 images, collected at a depression angle of 17 degrees.

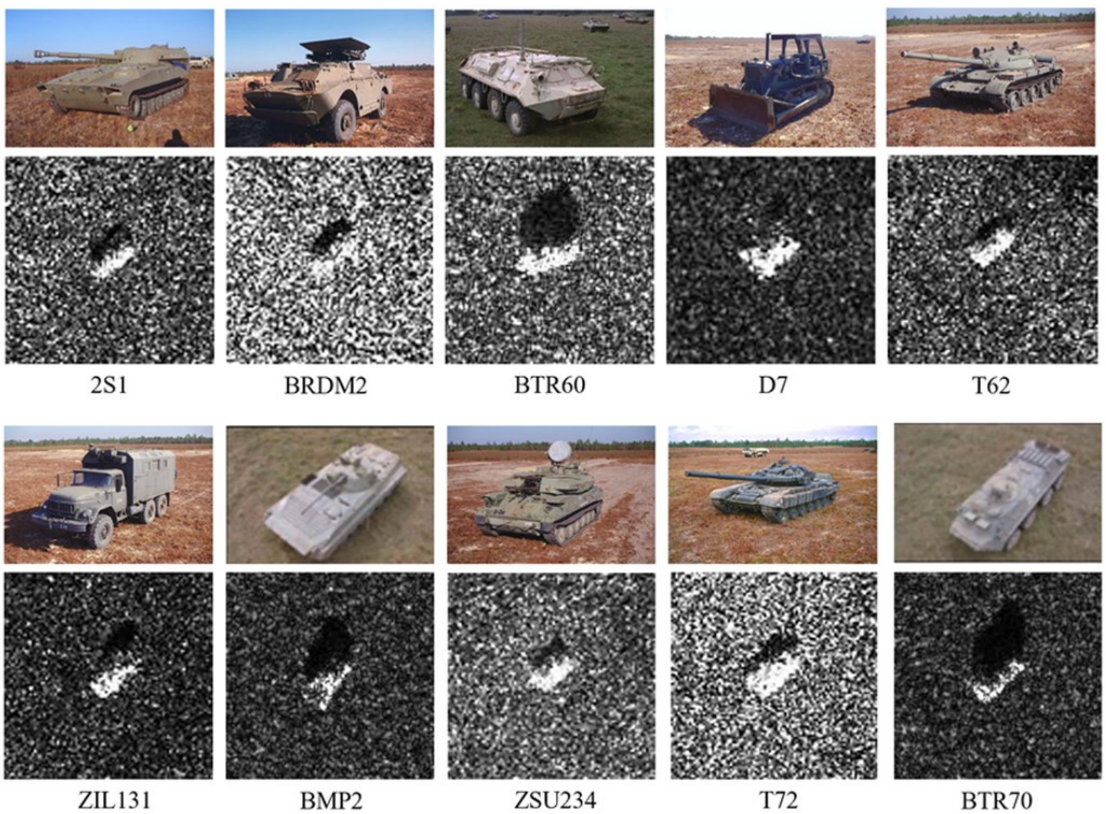


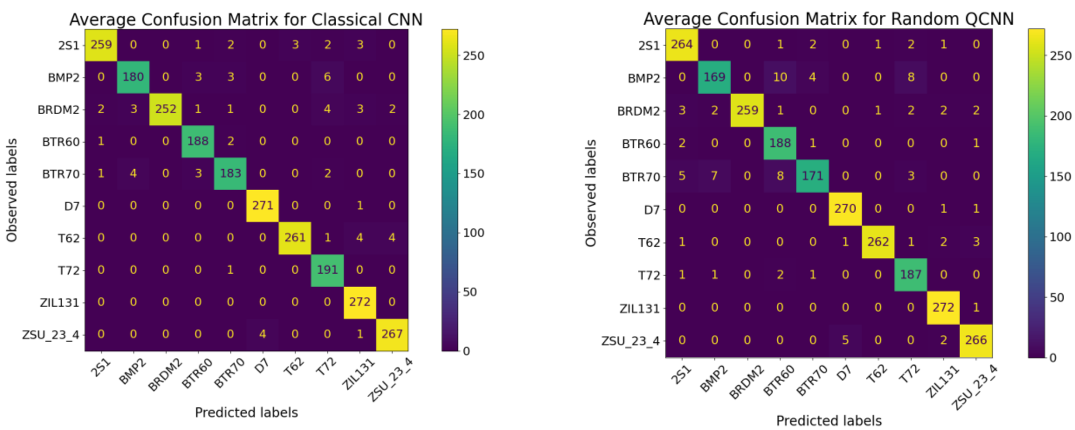
Figure 4. Military ground targets from the MSTAR dataset. SAR images below with corresponding optical images above.
CC BY-NC-ND 4.0 DEED license [27]

3. RESULTS

Table 2 shows the results of our Monte Carlo trials. Confusion matrices are provided in Figure 5. We note that the random quantum classifier under ideal noise conditions shows no significant performance degradation when compared to the traditional classifier. This observation adds validity to the claims seen in [18] when extending to new datasets and differing modalities. We note that while our experiments assumed ideal noise conditions, previous work has shown we can expect a performance decrease of ~2% when factoring noise into the simulations [24].

Table 2: Results of Monte Carlo Trials

	Number of Trials	Accuracy Mean	Accuracy Stdev
Traditional Classifier	20	0.96	0.012
Random Quantum Classifier	5	0.95	0.017



(a) Traditional Classifier (b) Random Quantum Classifier

Figure 5: Confusion matrices showing true classifications and confusers for both the hybrid and classical CNN models. Notice that all classes were recognized and classified well with no pairs causing substantial confusion.

Even given the expectation of lowered performance due to noise in a more realistic environment, these results are quite positive. In the future, SAR classification can benefit from the expected speed-up that quantum computing promises.

4. FUTURE WORK

The quantum simulations in this study were conducted in an "ideal" simulator without considering the effects of quantum noise. Thus, these results may not necessarily represent the true performance of this algorithm on real quantum hardware. The current era of Noisy Intermediate-Scale Quantum (NISQ) computers has inherent noise and precision issues which decrease the performance of quantum machine learning algorithms. Specially designed circuits or error mitigation techniques can be used to counteract these issues, however with limited efficacy. In the future, we plan to explore these techniques and the effects of noise on the algorithms used in this study in order to determine a more realistic accuracy given the current state of quantum hardware.

While performance seems to be consistent between hybrid and traditional CNNs, future efforts will aim to improve hybrid performance by utilizing a customized, deterministic quantum convolutional filter. Custom circuits will be designed with the intention of improving results when simulating with realistic quantum noise. While preliminary designs in small-scale tests have yielded slightly lower accuracies than the methods explored in this study, more work must be done to refine and optimize these designs to improve performance.

The design of the overall model could also be optimized for increased performance. While this study focused on a relatively small convolutional model, future work could explore deeper CNN's and QCNN's for increased accuracy. Previous studies suggest that a deeper model could enhance performance in classification tasks [18][24].

Other future work in this field includes expanding the scope of the quantum hybrid convolutional neural network proposed in this study to other applications in remote sensing. Working with datasets and sensing technologies beyond SAR could offer more insight into the applications of QML in remote sensing. Additional work in the future includes exploiting the properties of Positive Unlabeled (PU) Learning in QML. PU learning provided promising results [28] in several other classical computing applications addressed before by our teams at ASU and PSG.

5. CONCLUSION

We have designed a series of quantum machine learning circuits and have shown specifically the feasibility of using quantum convolutional filters for SAR image classification. Accuracy of a quantum-traditional hybrid CNN with random weights showed no significant change in performance from that of a classical CNN in the absence of quantum noise. Our findings act as another data point bolstering the functionality of the quantum convolutional algorithm. As quantum hardware and algorithms advance, we anticipate transferability of the quantum convolutional algorithm for SAR classification to quantum systems.

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REFERENCES

[1] P. Knee, J. J. Thiagarajan, K. N. Ramamurthy and A. Spanias, "SAR target classification using sparse representations and spatial pyramids," *in Proc. of IEEE Radar Conference (RADAR),* pp.294-298, 2011.

[2] C. Coman and R. Thaens, "A Deep Learning SAR Target Classification Experiment on MSTAR Dataset," 2018 19th International Radar Symposium (IRS), Bonn, Germany, 2018, pp. 1-6, doi: 10.23919/IRS.2018.8448048.

[3] S. Chen and H. Wang, "SAR target recognition based on deep learning," DSAA 2014 - *Proc. 2014 IEEE Int. Conf. Data Sci. Adv. Anal*., pp. 541–547, 2014.

[4] Y. Zhang, X. Sun, H. Sun, Z. Zhang, W. Diao, and K. Fu, "High resolution SAR image classification with deeper convolutional neural network," Int. Geosci. Remote Sens. Symp., vol. 2018-July, pp. 2374–2377, 2018.

[5] Y. Li, X. Li, Q. Sun, and Q. Dong, "SAR Image Classification Using CNN Embeddings and Metric Learning," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, pp. 1–5, 2022.

[6] Z. Huang, Z. Pan, & B. Lei, "Transfer learning with deep convolutional neural network for SAR target classification with limited labeled data", *Remote Sensing,* vol. 9, no. 9, p. 907, 2017. https://doi.org/10.3390/rs9090907

[7] H. Pei, M. Su, G. Xu, M. Xing, and W. Hong, "Self-Supervised Feature Representation for SAR Image Target Classification Using Contrastive Learning," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens*., vol. 16, no. X, pp. 9461–9473, 2023.

[8] N. Vaughn, B. Sullivan, & K. Jaskie, "Unsupervised SAR representation learning improves classification performance". *SPIE Defense and Commercial Sensing,* April 2024 .

[9] A. Moreira, P. Prats-Iraola, M. Younis, G. Krieger, I. Hajnsek, and K. P. Papathanassiou, "A tutorial on synthetic aperture radar," *IEEE Geosci. Remote Sens. Mag*., vol. 1, no. 1, pp. 6–43, 2013.

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

[11] M. Schuld, I. Sinayskiy, and F. Petruccione, “An introduction to quantum machine learning*,” Contemp. Phys*., vol. 56, no. 2, pp. 172–185, 2015.

[12] Y. Y. Hou, J. Li, X. B. Chen, and C. Q. Ye, “Quantum adversarial metric learning model based on triplet loss function,” EPJ Quantum Technol., vol. 10, no. 1, pp. 1–16, 2023.

[13] V. Havlíček et al., “Supervised learning with quantum-enhanced feature spaces,” Nature, vol. 567, no. 7747, pp. 209–212, 2019.

[14] F. Marquardt, “Machine learning and quantum devices,” SciPost Phys. Lect. Notes, vol. 29, no. 29, pp. 1–44, 2021.

[15] S. Saeedi, A. Panahi, and T. Arodz, “Quantum semi-supervised kernel learning,” *Quantum Mach. Intell*., vol. 3, no. 2, pp. 1–18, 2021.

[16] K. Mitarai, M. Negoro, M. Kitagawa, and K. Fujii, “Quantum circuit learning,” *Phys. Rev. A,* vol. 98, no. 3, pp. 1–3, 2018.

[17] M. H. Amin, E. Andriyash, J. Rolfe, B. Kulchytskyy, and R. Melko, “*Quantum Boltzmann Machine*,” Phys. Rev. X, vol. 8, no. 2, p. 21050, 2018.

[18] M. Henderson, S. Shakya, S. Pradhan, & T. Cook, "Quanvolutional neural networks: powering image recognition with quantum circuits", *Quantum Machine Intelligence,* vol. 2, no. 1, 2020. https://doi.org/10.1007/s42484-020-00012-y

[19] R. Parthasarathy and R. Bhowmik, "Quantum optical convolutional neural network: a novel image recognition framework for quantum computing", *IEEE Access*, vol. 9, p. 103337-103346, 2021. https://doi.org/10.1109/access.2021.3098775

[20] W. Li, P. Chu, G. Liu, Y. Tian, T. Qiu, & S. Wang, "An image classification algorithm based on hybrid quantum classical convolutional neural network", *Quantum Engineering*, vol. 2022, p. 1-9, 2022. https://doi.org/10.1155/2022/5701479

[21] S. Wei, Y. Chen, Z. Zhou, & G. Long, "A quantum convolutional neural network on nisq devices", *AAPPS Bulletin*, vol. 32, no. 1, 2022. https://doi.org/10.1007/s43673-021-00030-3

[22] I. Cong, S. Choi, and M. D. Lukin, “Quantum convolutional neural networks,” *Nat. Phys*., vol. 15, no. 12, pp. 1273–1278, 2019.

[23] L. Miller, G. Uehara, A. Sharma, and A. Spanias, “Quantum Machine Learning for Optical and SAR Classification,” *IEEE Int. Conf. Digit. Signal Process. DSP*, vol. 2023-June, 2023.

[24] L. Miller, G. Uehara, and A. Spanias, “Quantum Image Fusion Methods for Remote Sensing,” *IEEE Aerospace Conference*, Big Sky, Montana, March 2024.

[25] https://pennylane.ai/

[26] https://www.kaggle.com/datasets/ravenchencn/mstar-10-classes

[27] H. Pei, M. Su, G. Xu, M. Xing, and W. Hong, “Self-Supervised Feature Representation for SAR Image Target Classification Using Contrastive Learning*,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens*., vol. 16, no. X, pp. 9461-9473, 2023.

[28] K. Jaskie and A. Spanias, *Positive Unlabeled Learning*, Morgan & Claypool Publishers (now Springer Nature), AI and Machine Learning Eds. R. Brachman and F, Rossi 152 pages, ISBN 9781636393087, In print Spring 2022.