QUANTUM IMAGE FUSION FOR REMOTE SENSING

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Agenda

- Research Overview
- Previous Work
- Quantum Fusion Approach
- Results
- Conclusion

Research Overview

- Scene classification of C-band SAR and optical images
  - Images are split into four subcategories: barren land, grassland, urban, and agriculture
- Use quantum fusion techniques for image pre-processing
- Applications for this work include surveillance, navigation, space exploration, iceberg and weather tracking, and surveying the effects of global warming [1]

Main Goal: Use quantum and classical techniques to analyze data from satellites

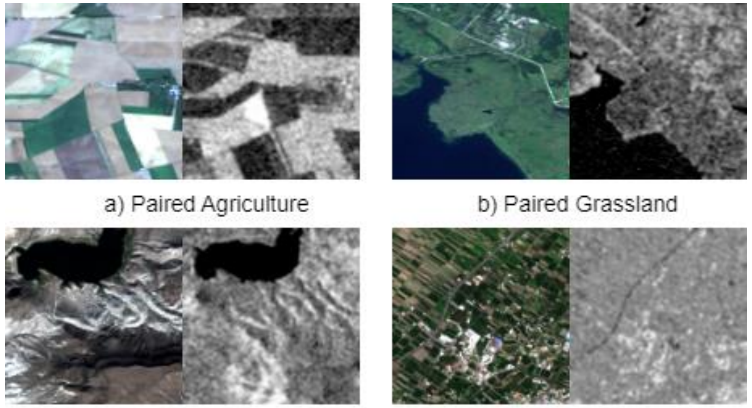
Synthetic Aperture Radar (SAR)

- SAR is an active data collection method, where the sensor generates its own energy and measures the energy reflected [2]
- SAR is complex to process and has speckle effects
  - Need a way to extract important details from the SAR image
  - Feature extraction and feature fusion has shown promising results

Advantages of SAR	Limitations of SAR
Sensitive to man-made objects	Complex processing
Can depict surface depths	Difficult to Interpret Data
Independent of light conditions	Speckle effects
Independent of weather conditions	Effects of Surface Roughness

Dataset

- The Sentinel satellites are a part of the Copernicus Space Program of European Space Agency (ESA) [3]
  - The main goal of this program is to ensure data continuity for applications in ocean, atmosphere, and land monitoring
- The SEN 1-2 dataset consists of pairs of corresponding image patches
  - These images are collected across the globe and include various meteorological seasons, including summer and fall

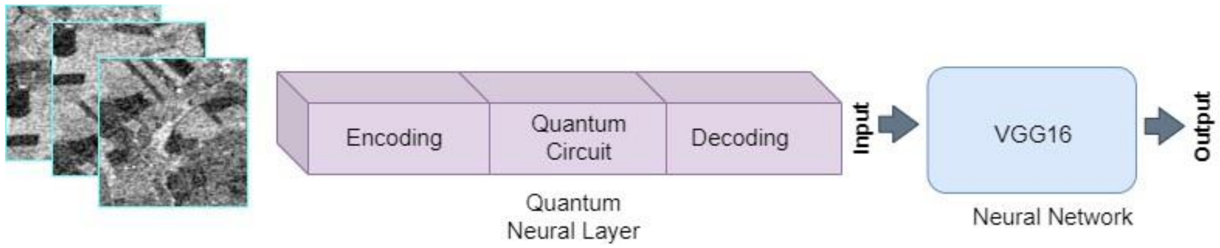


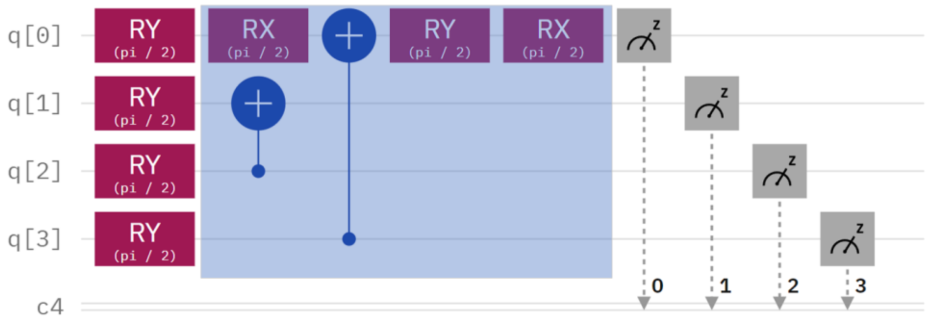
a) Paired Agriculture b) Paired Grassland c) Paired Barrenland d) Paired Urban

PREVIOUS WORK

QCNN for SAR Classification

- Analysis of classical classification methods vs. quantum methods for the SAR dataset
- Utilized "Quanvolutional" neural networks for quantum classification
  - Classification accuracy of 72% for classical method and 60% for quantum method [4]

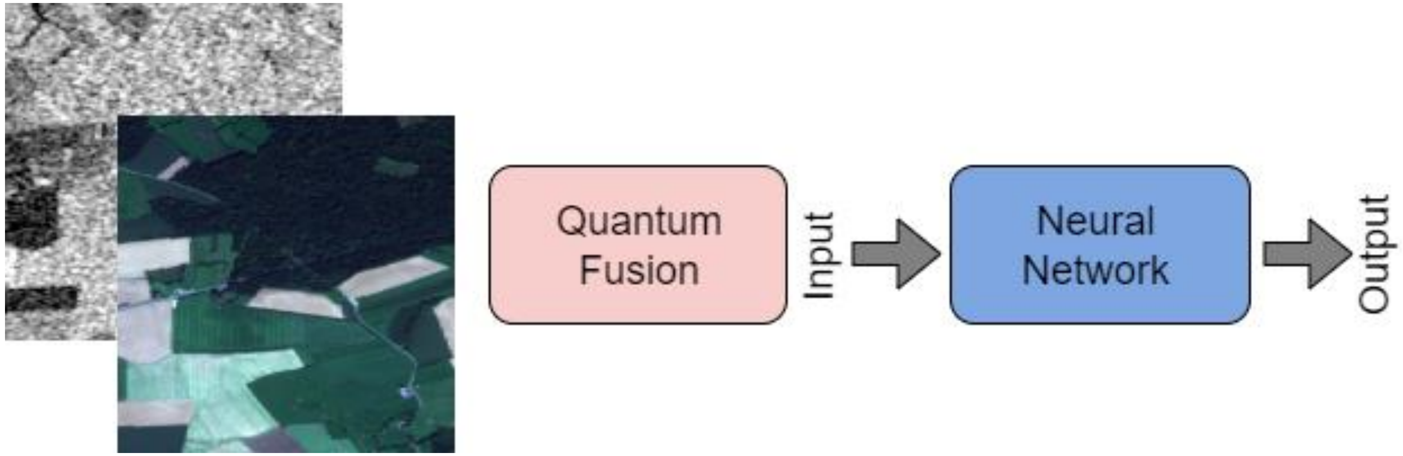




QUANTUM FUSION APPROACH

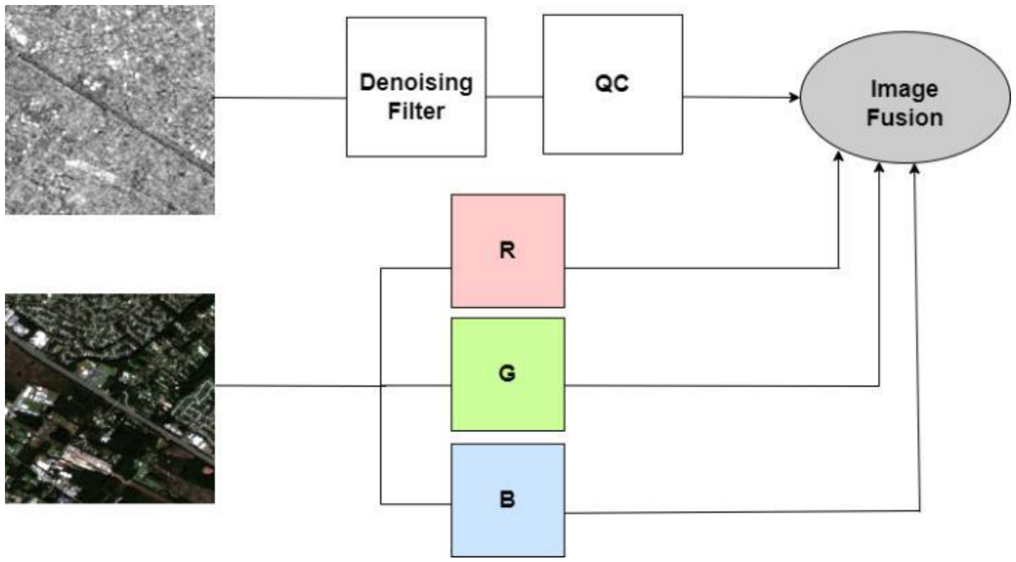
Overall Approach

- Perform two different classical and two quantum fusion methods
- Propose a new four qubit quantum circuit for processing of the SAR images
- Utilize classical convolutional neural networks to perform scene classification
- Compare the results for the classical and quantum methods [5,6]



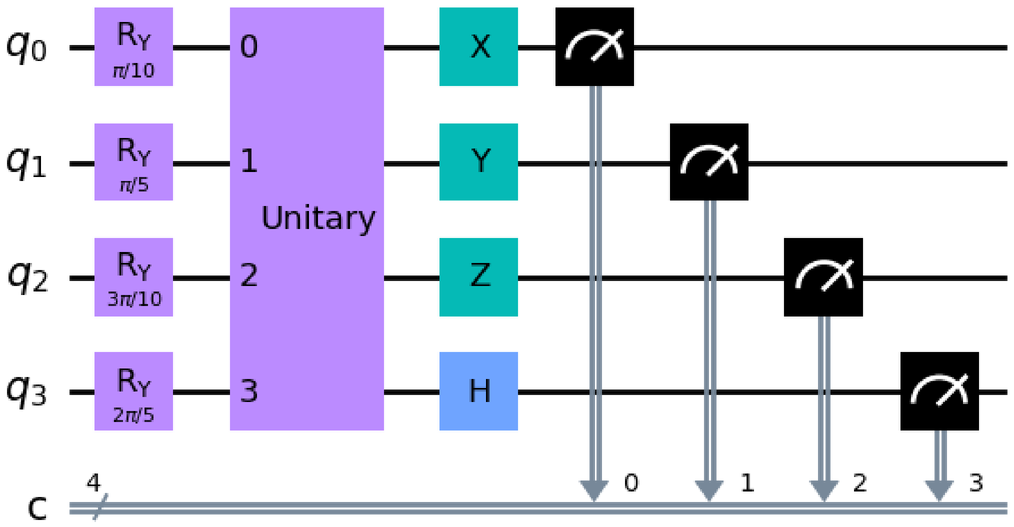
Quantum Fusion

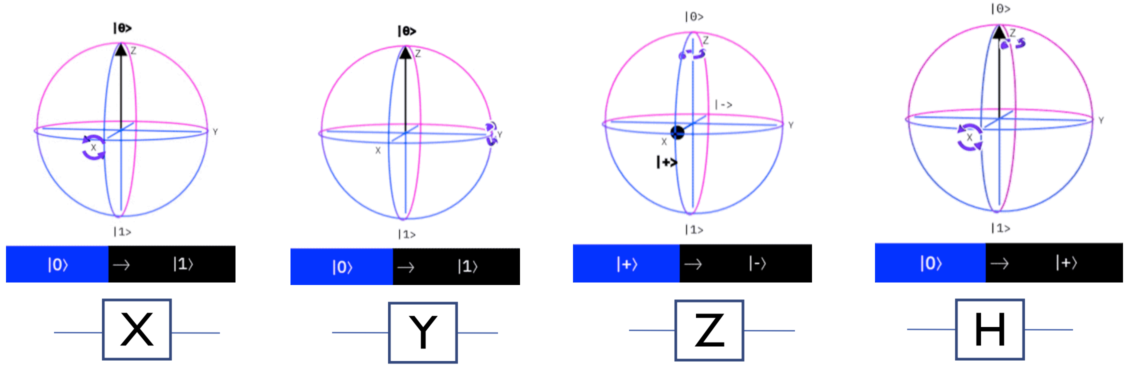
- Steps:
  - Add a denoising filter to SAR dataset
  - Split the optical dataset into three channels (red, green, and blue)
  - Process the SAR dataset using a four-qubit quantum circuit (QC)
  - Mathematical fusion



Quantum Circuit

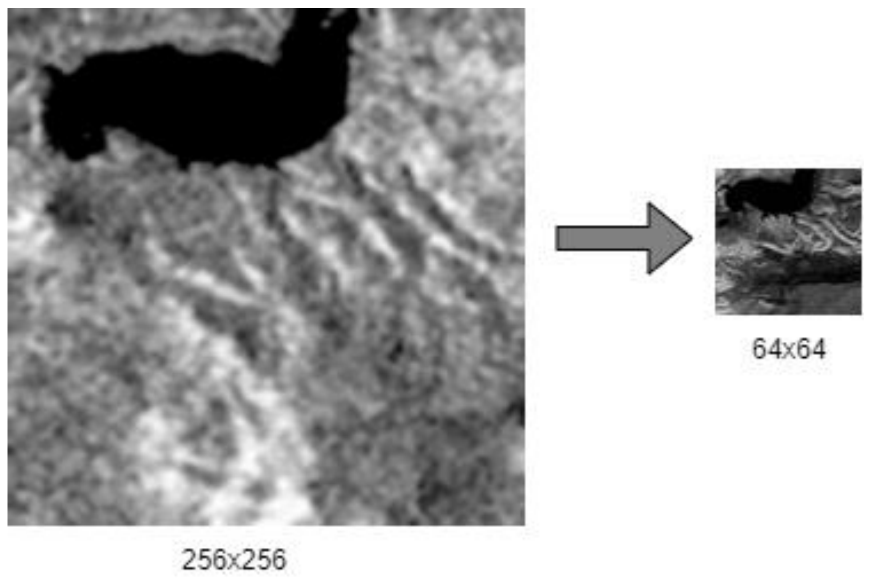
- Used a 4-qubit, 2-layer quantum circuit
  - Initially ran randomized gates on each of the qubits to identify which random set of gates produced the best result



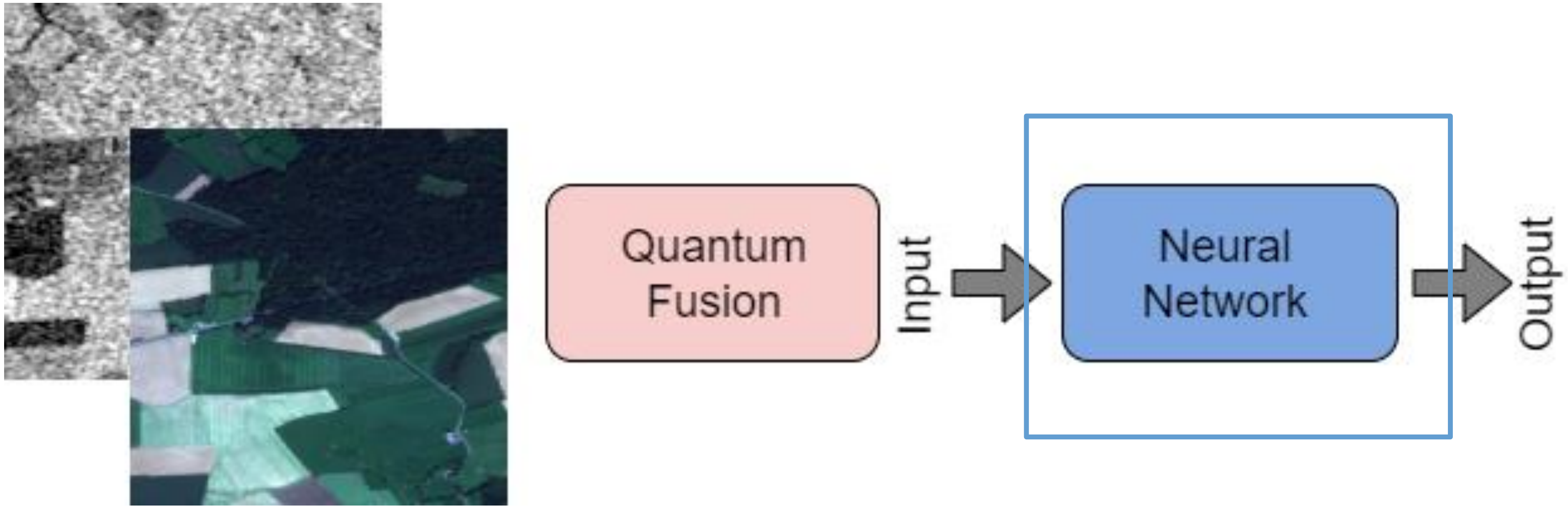


Quantum Fusion Result

- Using quantum fusion, we go from a 256x256 image to a 64x64 quantum fused image

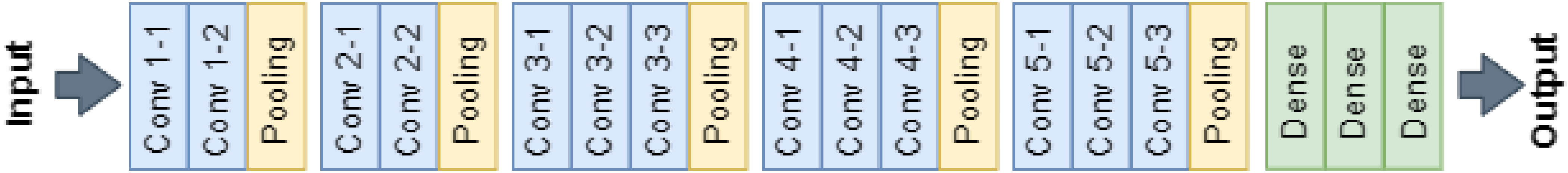


Neural Network



Neural Network Architecture

- The Visual Geometry Group 16 (VGG16) is a standard deep convolutional neural network consisting of multiple layers[7]
  - The VGG16 consists of thirteen convolutional layers and three fully connected layers
- Keras machine learning package is used to perform machine learning [8]
  - Adam optimizer
  - Classified four classes of images



Fusion Results

Method	Data Size	Accuracy %
Classical Fusion Method I	Train: 3200 Validation: 800	Train: 93.09 Validation: 83.84
Classical Fusion Method II	Train: 3200 Validation: 800	Train: 85.55 Validation: 68.78
Quantum Fusion Method II	Train: 3200 Validation: 800	Train: 88.96 Validation: 75.42
Quantum Fusion Method III	Train: 3200 Validation: 800	Train: 94.64 Validation: 86.79

Challenges using Quantum Fusion

Challenges of Quantum Fusion
Long processing times
Limited availability of qubits
Only have access to simulators

Advantages using Quantum Fusion

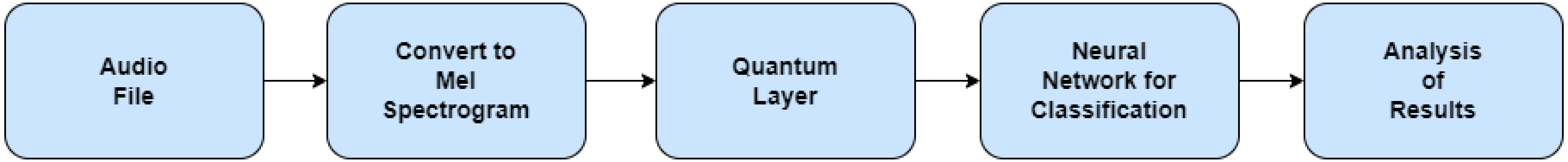
Advantages of Quantum Image Fusion
Reduction in Computational Complexity (relative to our other study)
Reduction in Memory
Higher Classification Accuracy
Use of lower resolution images

Comparison of Techniques

Method	Accuracy % (train vs. validation)
Classical Fusion	Train: 93.09 Validation: 83.84
Quantum Fusion	Train: 94.68 Validation: 86.29
Classical VGG16	Train: 77.19 Validation: 72.50
VGG+Quanvolution	Train: 66.72 Validation: 59.38

Future Work

- Examine other quantum fusion methods and neural networks to increase classification accuracy
- QML for audio classification purposes



Conclusion

- Proposed a novel way to use quantum circuits to process the SAR dataset
- Performed image fusion and classification using machine learning
- Compared the accuracy of the quantum image fusion to classical image fusion
- We found that the overall quantum fusion system has shown promising results and has proven to have multiple advantages

THANK YOU

References

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

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[6] my paper

[7] G. Learning, “Everything you need to know about VGG16,” Medium, 23-Sep-2021. [Online]. Available: https://medium.com/@mygreatlearning/everything-you-need-to-know-about-vgg16-7315defb5918. [Accessed: 07-Mar-2023].

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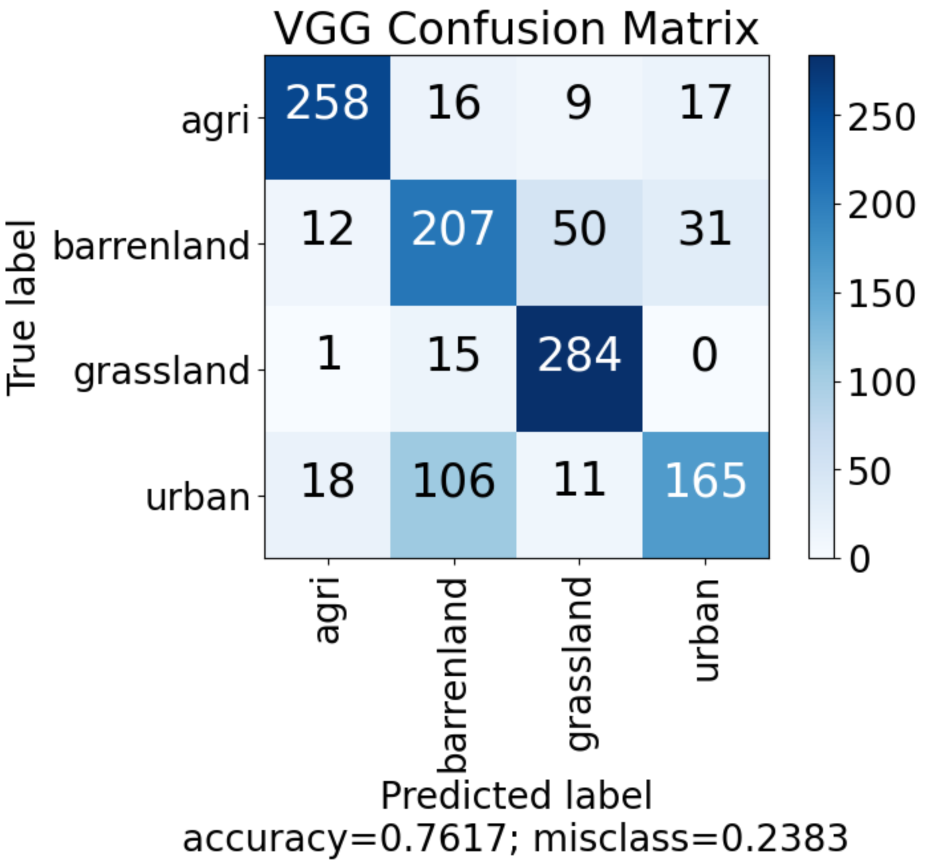
ADDITIONAL SLIDES

Classical ML Results

VGG16 SAR Dataset



Equations

$$Red\_new = (R/(R+G+B))*S \quad (1)$$

$$Blue\_new = (B/(R+G+B))*S \quad (2)$$

$$Green\_new = (G/(R+G+B))*S \quad (3)$$

$$MF=stack(Red\_new, Blue\_new, Green\_new) \quad (4)$$

Method II

The second classical fusion method can be seen in equations 5,6,7.

$$Red\_new =(S+3*R)/4 \quad (5)$$

$$Blue\_new =(S+3*B)/4 \quad (6)$$

$$Green\_new =(S+3*G)/4 \quad (7)$$

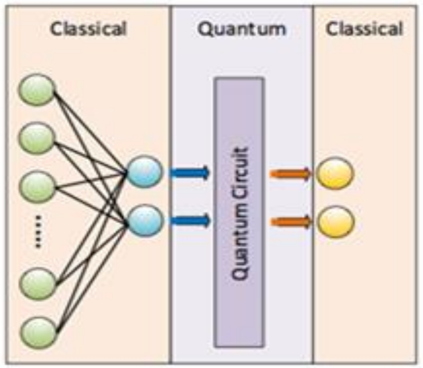
Method III

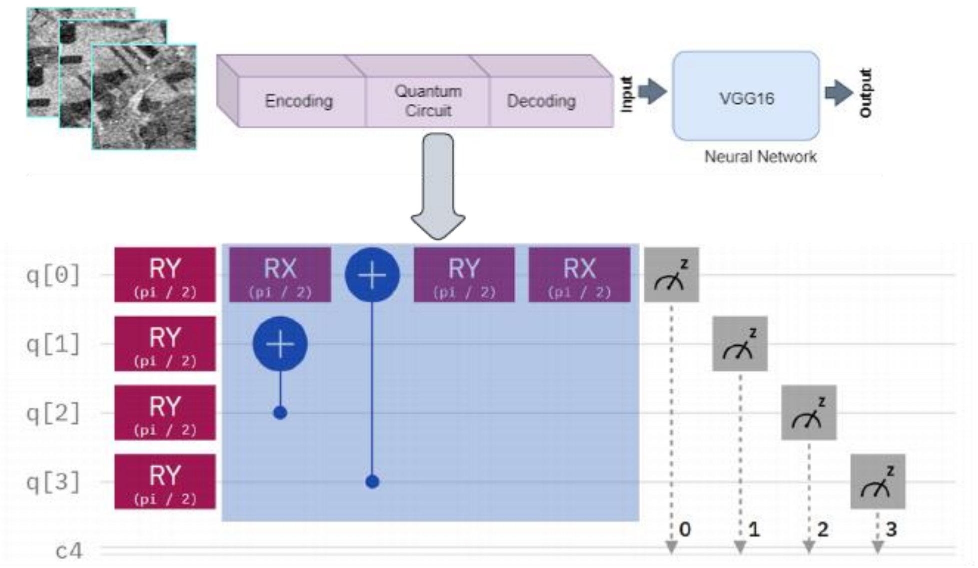
Method III uses averaging to perform image fusion [5].The equation for Method III can be found in Equation 8 where R=red, B=blue, G=green, and S=SAR.

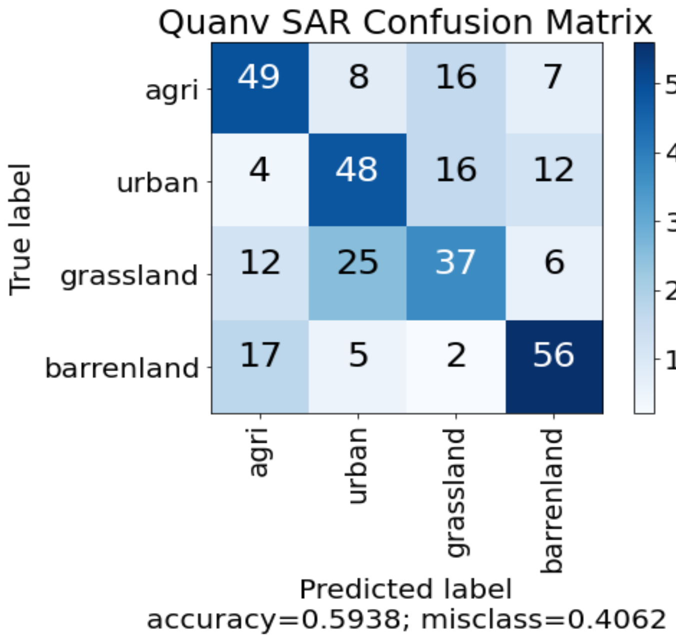
$$(S+R+G+B)/4 \quad (8)$$

Quanvolutional Neural Network

- In our neural network design, we added a quantum neural layer at the beginning to determine if encoded features can be extracted from the images

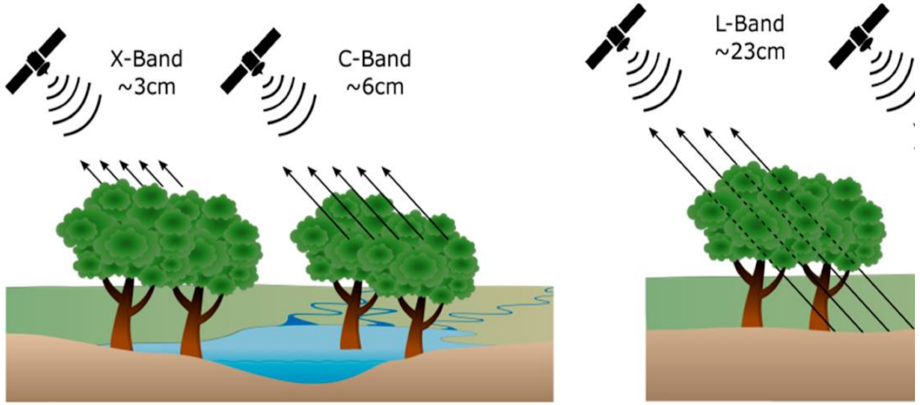


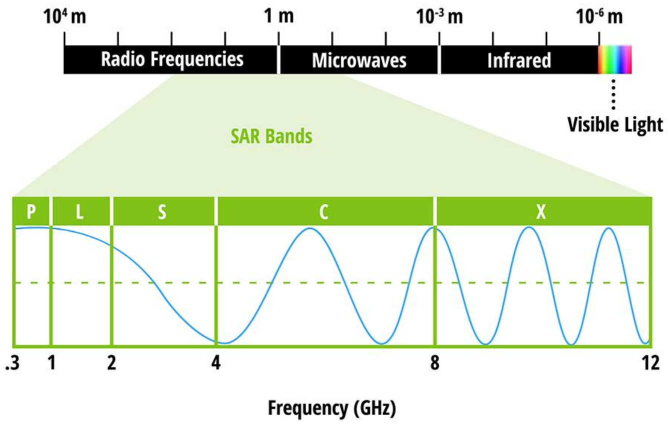




Synthetic Aperture Radar (SAR)

- SAR sensors use wavelengths ranging from P-band to Ka-band
- C-band has bit more penetration capability than X-Band
  - L- and P-bands penetrate foliage and may even illuminate ground features under the tree canopy
- Typical applications for C-Band are global mapping, change detection, monitoring areas with low to moderate penetration, ocean maritime navigation,

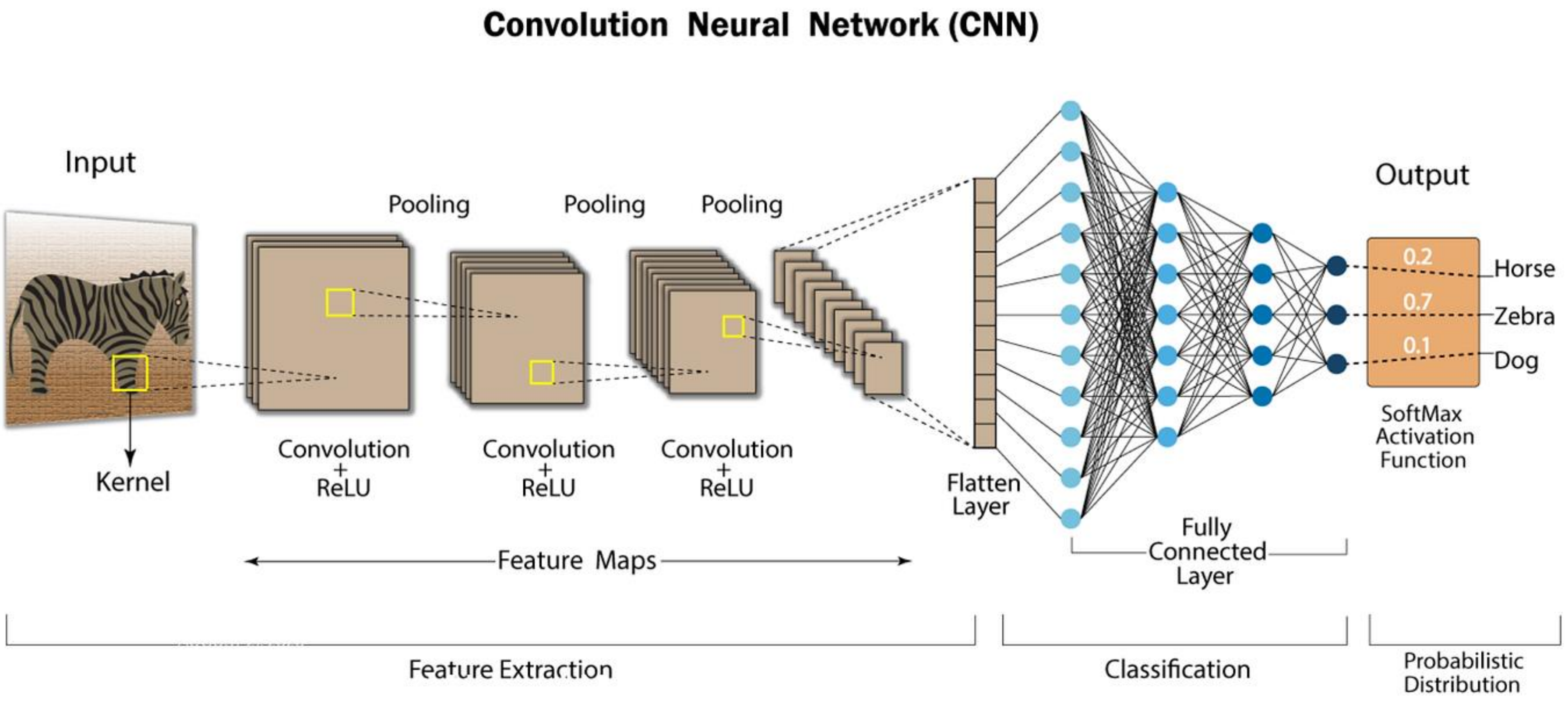




Optical Images

- Optical sensors are passive, gathering information in the visible and near-infrared sections of the electromagnetic spectrum
  - Depends on an external source of energy to collect data (passive sensor)
- Optical Imagery records radiance (reflectance/brightness)
- Measures light in the visible and infrared bands of the spectrum (wavelengths range from ~400 nm (blue) to ~2500 nm (shortwave infrared)
  - Images collected in the visible part of the spectrum can be combined to create RGB imagery (how we perceive the environment)

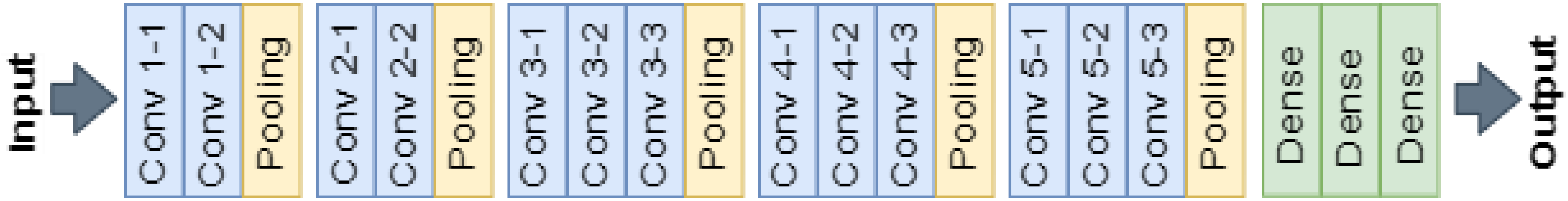
CNN’s



Convolution Neural Network (CNN)
Input
Kernel
Pooling
Pooling
Pooling
Convolution + ReLU
Convolution + ReLU
Convolution + ReLU
Feature Maps
Flatten Layer
Fully Connected Layer
Output
0.2
0.7
0.1
Horse
Zebra
Dog
SoftMax Activation Function
Feature Extraction
Classification
Probabilistic Distribution

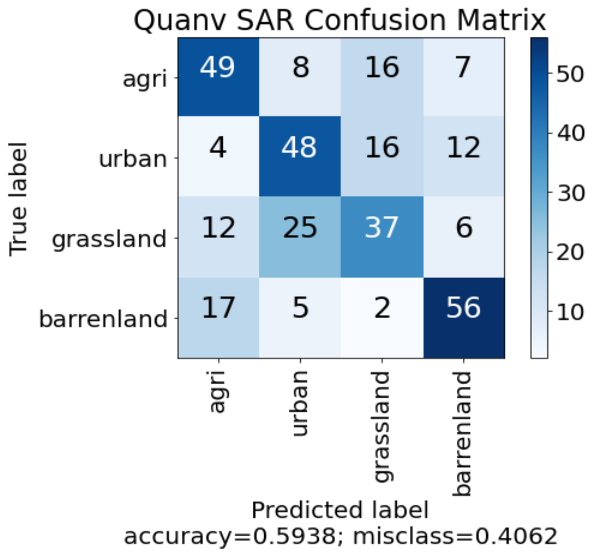
VGG16

- 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
  - It is one of the most popular image recognition architectures



Neural Networks Models and Training

- Quantum convolutional layers ("quanvolutional") are combined with a classical neural network model for the classification of SAR images into four classes
- 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



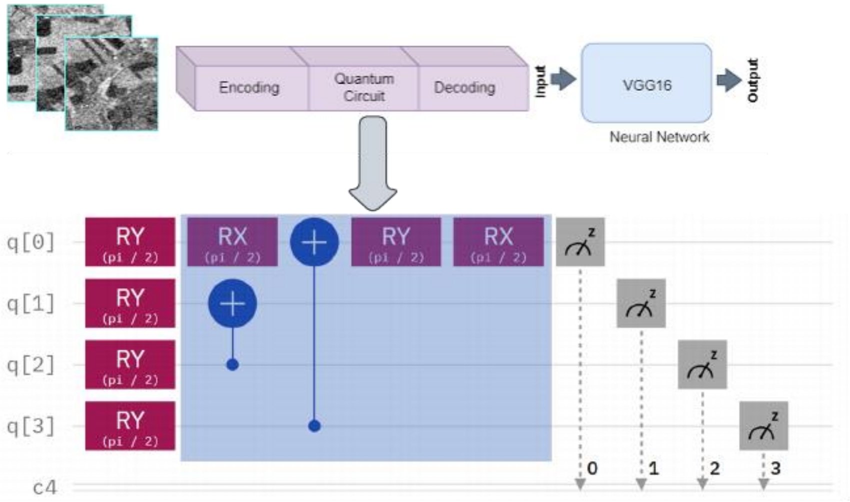
Results for QCNN

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

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

Quantum Circuit and Feature Extraction

- To perform feature extraction, we used a four-qubit quantum circuit
  - The circuit includes RY gates and Unitary gates
  - The Unitary gates are a set of gates with continuously changing weights that performs rotations
  - We ran randomized gates on each of the qubits to find which random circuit works the best



Quantum Gates

RY Gate: RY gate acts on a single qubit. Performs rotation about the Y-axis of the Bloch sphere by the given amount.
RX Gate: Rotation around the x-axis
Z Measurement: A measurement that provides information about the state of a qubit
CNOT Gate: Flips the state of the target qubit if and only if the control qubit is in the state |1>.