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ECMWF esa

Global Volcano Monitoring from Space with hybrid Quantum Convolutional Neural Networks

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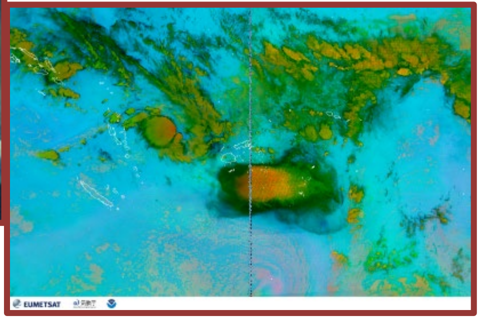
cmcc Centro Euro-Mediterraneo sui Cambiamenti Climatici

ThalesAlenia Space a Thales / Leonardo company

MOTIVATIONS

- **Earth Observation (EO) data** allow the **global monitoring of volcanic phenomena** and are crucial for aviation safety, hazard assessment, real-time eruption response, and evaluation of volcanic impacts on climate.
- Both **polar-orbiting** and **geostationary satellite sensors** provide observations that are well suited for detecting and recognizing both **slow and fast-evolving phenomena**, from the propagation of lava flows to the dispersion of volcanic clouds.

The growing volume of satellite data requires the development of **artificial intelligence (AI) techniques** to automatically retrieve synthetic information about the volcano condition in a very short time. **On-board processing** is increasingly being considered as a strategic solution to transmit critical information faster.



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MOTIVATIONS

Classical AI has limits in speed, complexity and data dimensions.

- **Quantum computing** could process vast solution spaces faster using quantum principles and less resources (computing capabilities and data size)
- Working in the **Hilbert Space** could shown new features extraction capabilities and resilience to geometric and morphological variations

QUANTUM MACHINE LEARNING

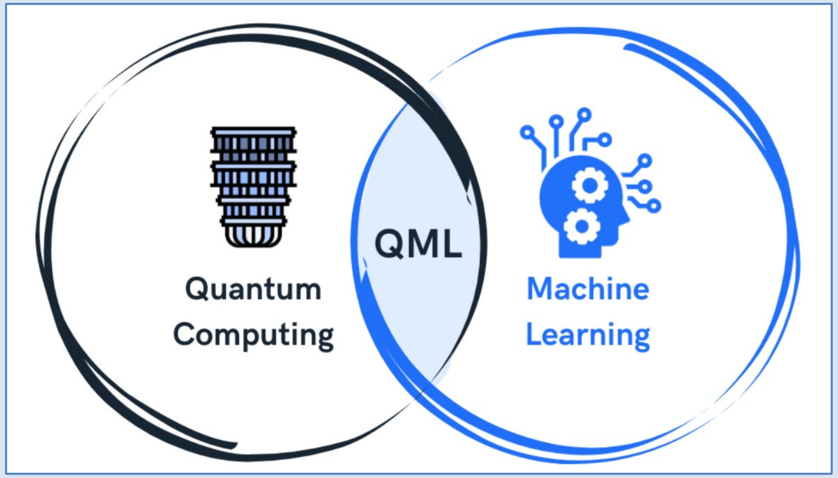

Image from https://www.ingenii.io/qml-blog/transformative-benefits-of-quantum-machine-learning

Intersection between Machine Learning (ML) and Quantum Computing (QC)

- Potential to improve the existing ML techniques
- Handling High-Dimensional Data
- Improved Generalization with Less Data

MOTIVATIONS

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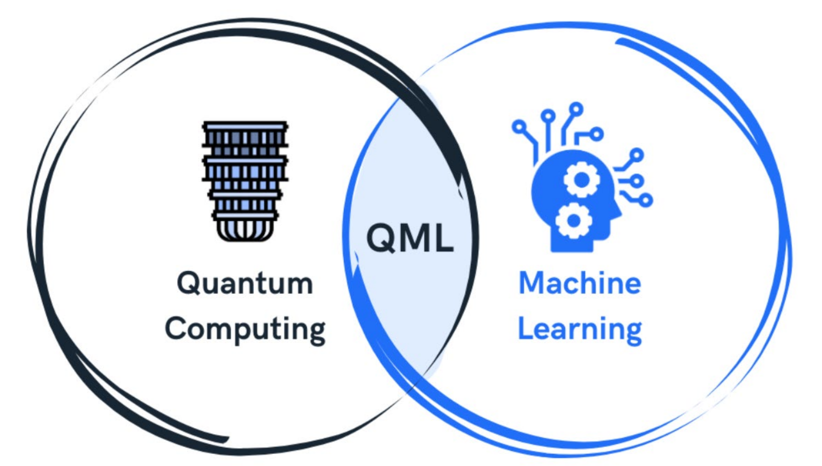


OBJECTIVE

Investigating the potential of circuit-based **hybrid Quantum Convolutional Neural Networks (QNN)** as image classifiers for classifying **volcanic activity** using Sentinel 2 MSI satellite data and identifying volcanic clouds in SEVIRI imagery.

Image from https://www.ingenii.io/qml-blog/transformative-benefits-of-quantum-machine-learning

SATELLITE SENSOR

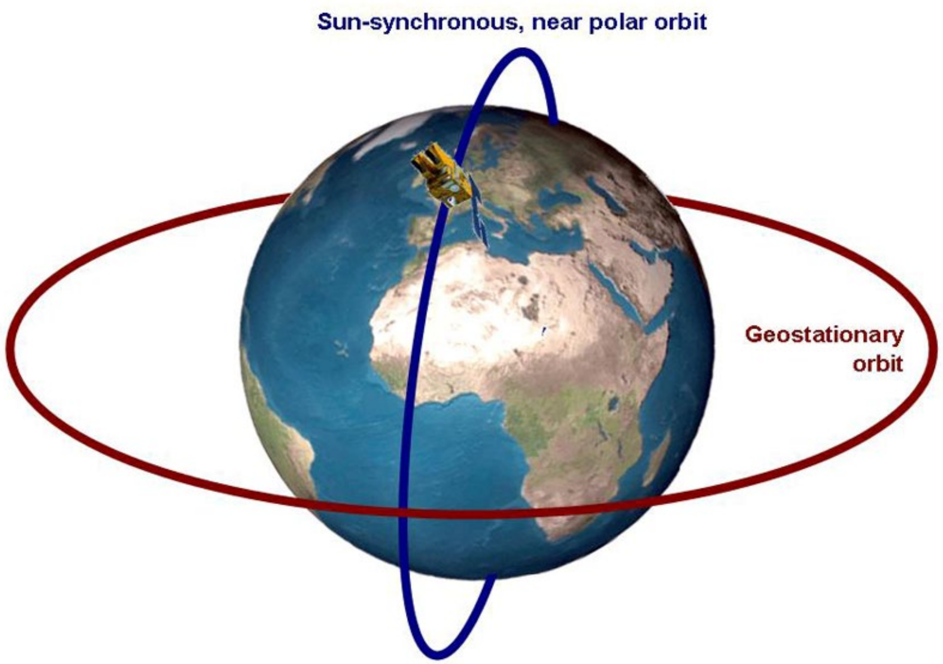


Image from https://seos-project.eu/remotesensing/remotesensing-c02-ws01-t.html

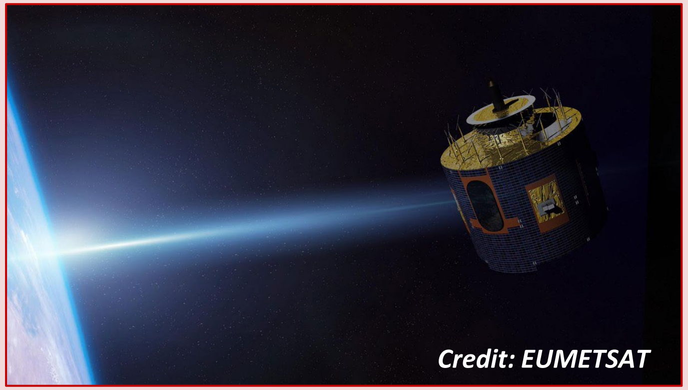
SENTINEL2: High Spatial Resolution (HSR) data

- Launched in 2015 and 2017: Sentinel-2A (S2A) and Sentinel-2B (S2B)
- Revisit frequency: 10 days (one satellite), 5 days (S2A+S2B)
- **MultiSpectral Instrument (MSI)**: 13 spectral bands (10m spat. res. visible, near infrared, 20m red edge, shortwave infrared)

Credit: ESA

METEOSAT SECOND GENERATION (MSG): High Temporal Resolution (HTR) data

- Launched in 2022
- Revisit frequency: 15 minutes
- **Spinning Enhanced Visible and InfraRed Imager (SEVIRI)**: 12 spectral bands (3 km spat. res. visible, near infrared and infrared, 1 km spat. res. HRV)



Credit: EUMETSAT

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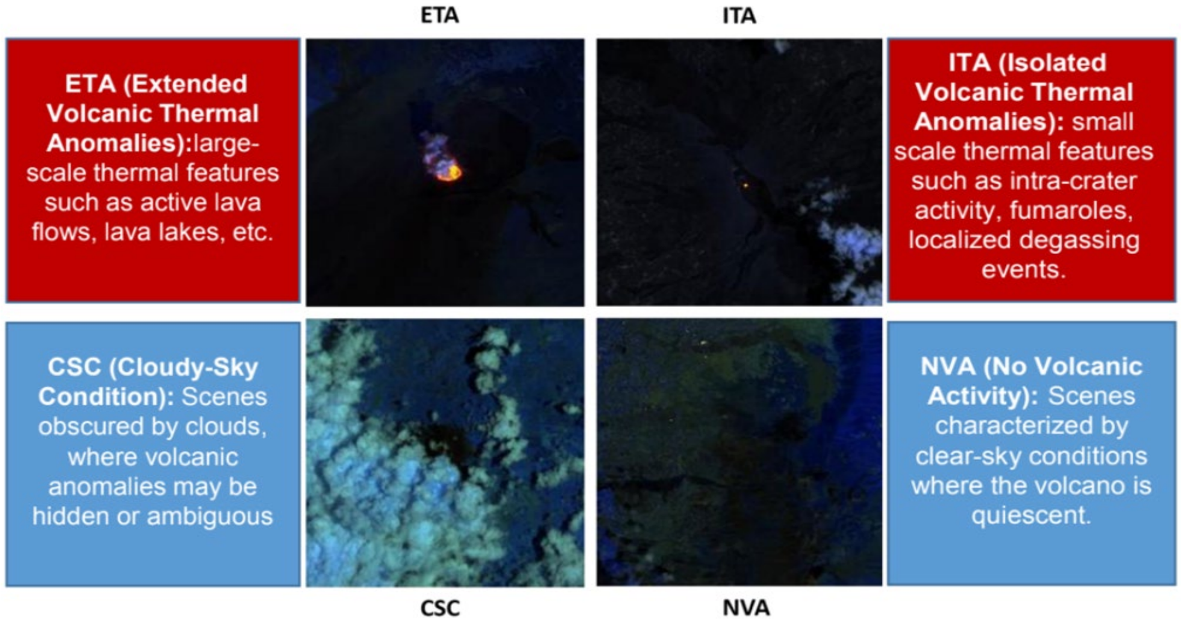
VOLCANIC PHENOMENA

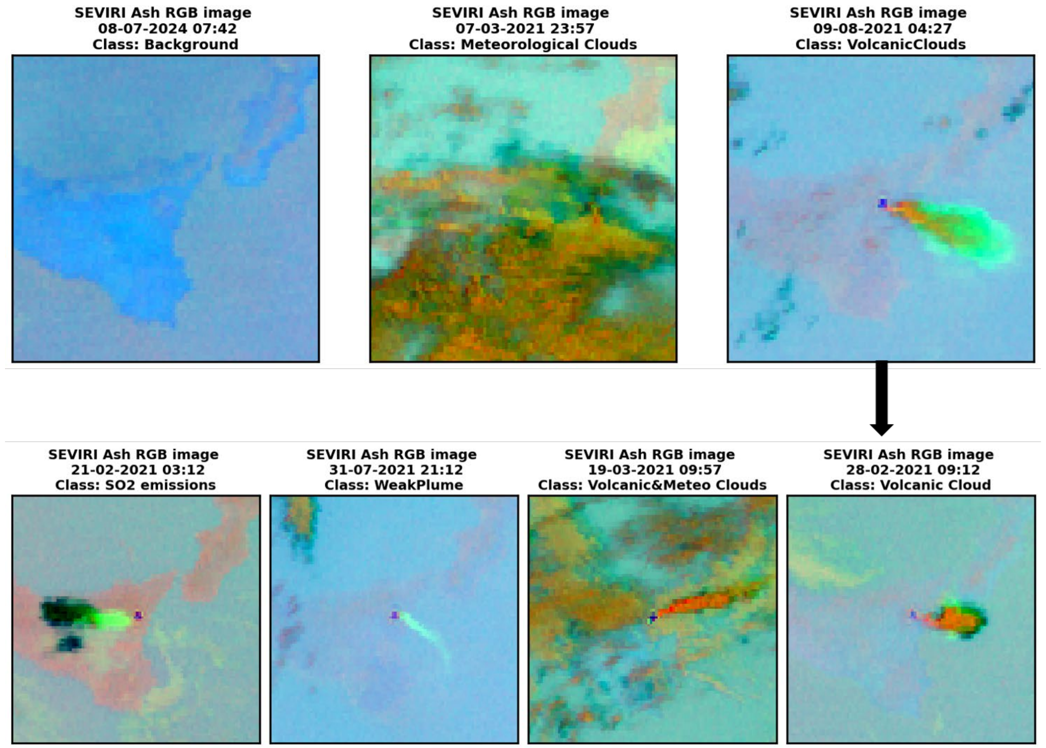
Slowly evolving volcanic phenomena:

Thermal volcanic activity classification using HSR

Rapidly evolving volcanic phenomena:

Volcanic Clouds Classification using HTR



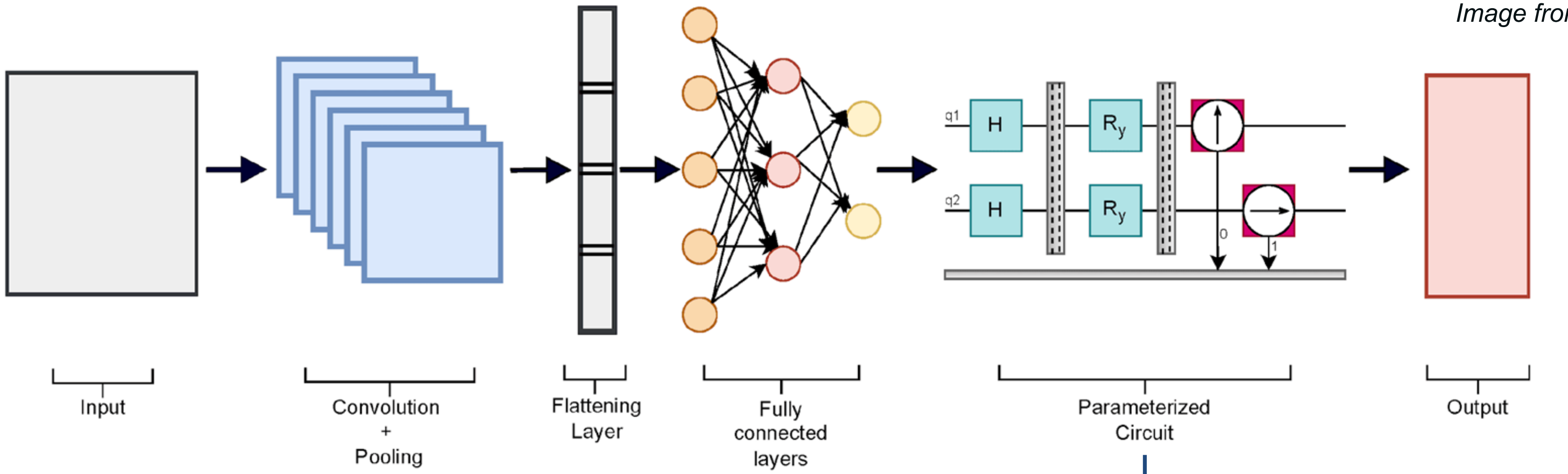


Cariello et al., 2023

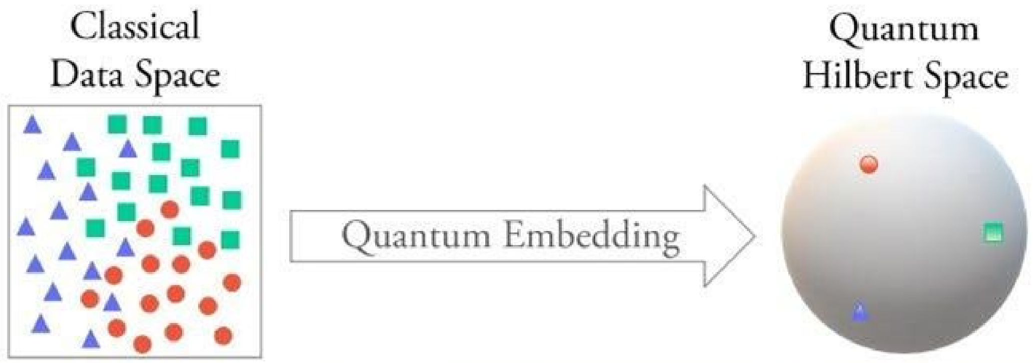
Torrisi et al., 2024

HYBRID QUANTUM CONVOLUTIONAL NEURAL NETWORK

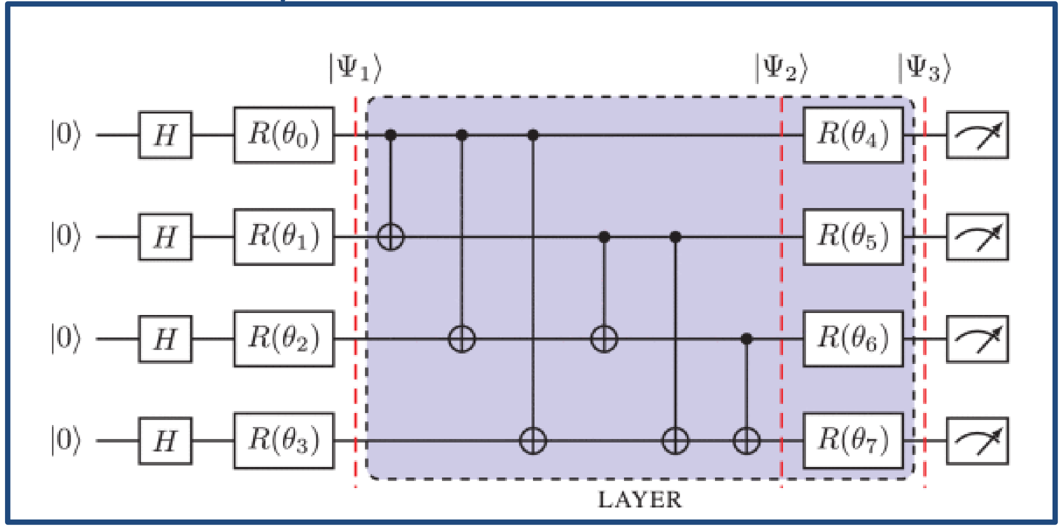
Image from Hafeez et al. (2024)



REAL AMPLITUDE CIRCUIT

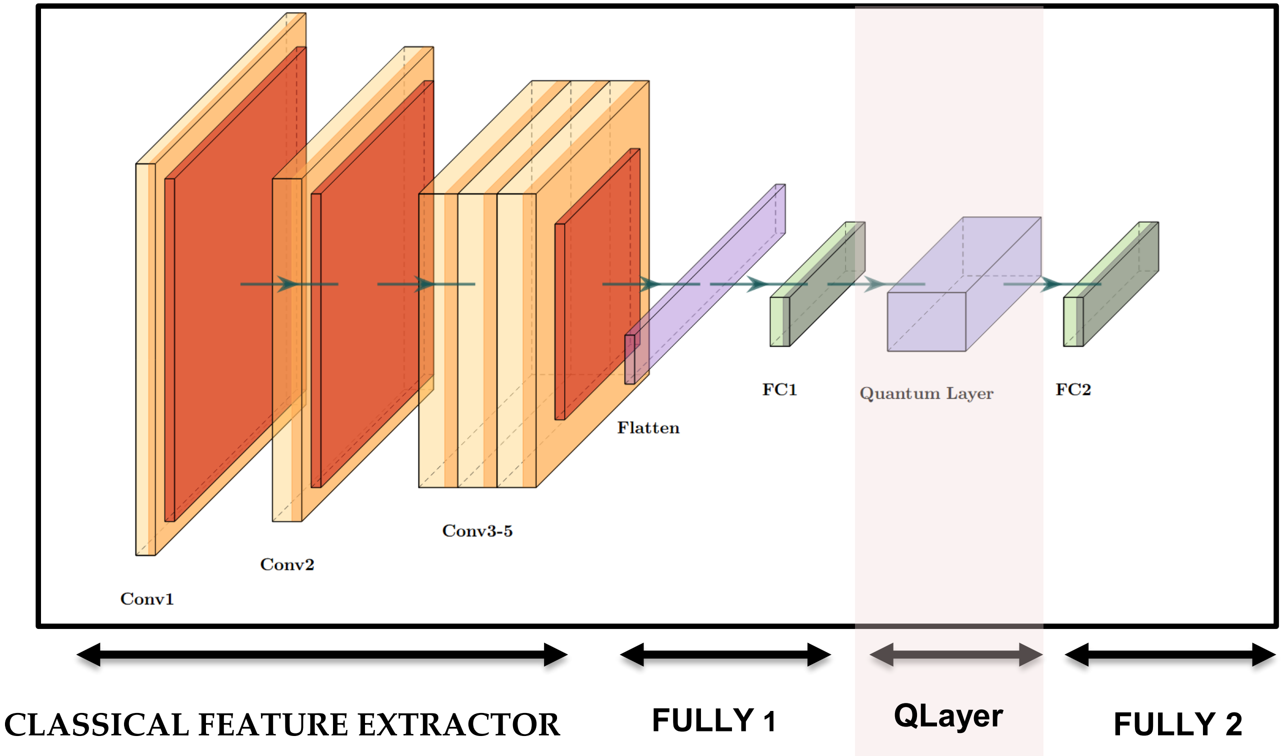


Images from Syed, S. (2021) 'Quantum Data and its Embeddings #1', Medium



Images from Sebastianelli et al. (2023)

METHODOLOGY



- **AlexNet**: five convolutional layers, ReLU Activations for accelerated training, max-pooling for spatial invariance, and dropout regularization to mitigate overfitting.
- **Fully 1**: serves to flatten the convolutional output and reduce its dimensionality to n features=quantum input
- **Quantum Layer**: Real Amplitude Circuit
- **Fully 2**: adapts the quantum output to match the number of classes

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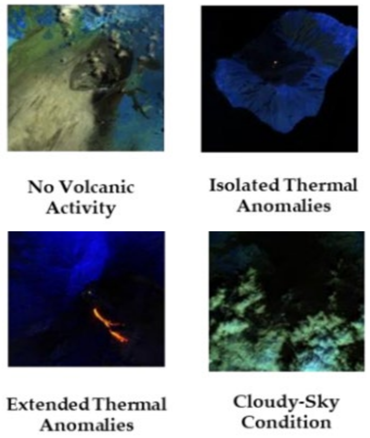
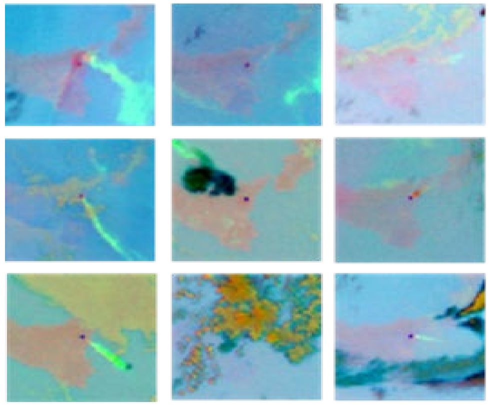
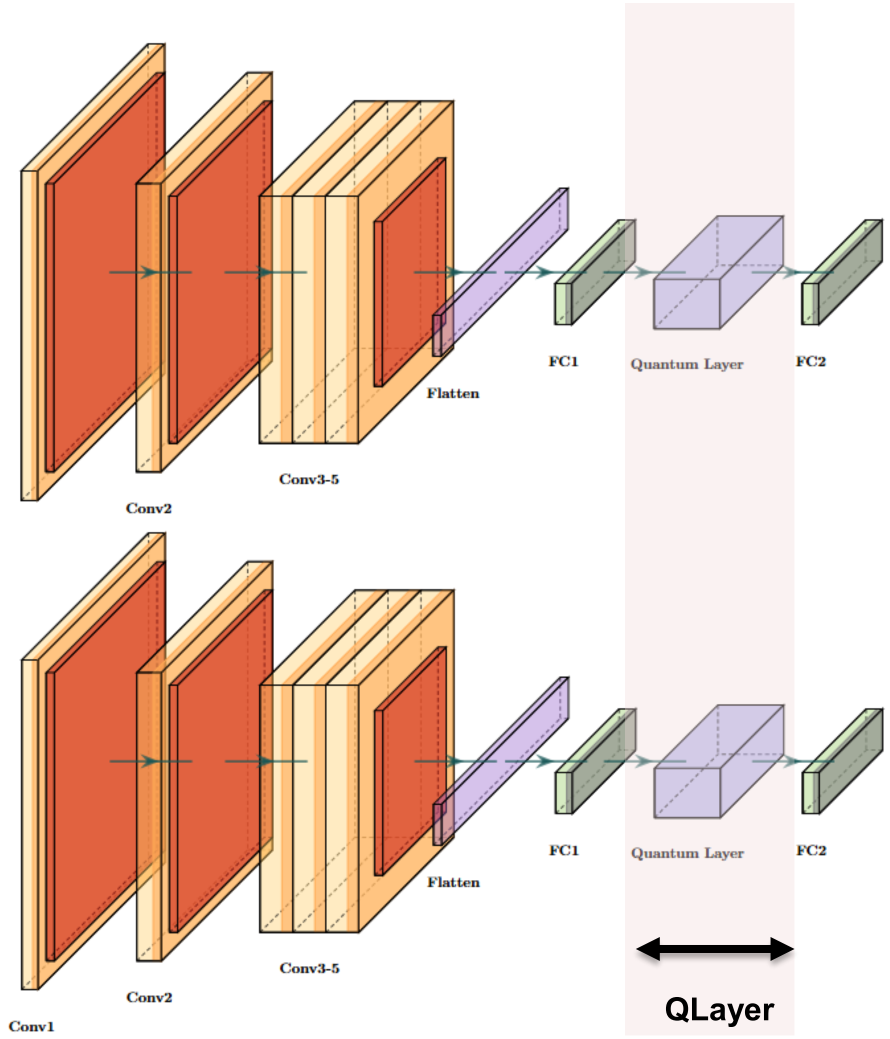
METHODOLOGY

Slowly evolving volcanic phenomena: thermal volcanic activity classification using HSR



Rapidly evolving volcanic phenomena: Volcanic Clouds Classification using HTR





Learning rate	Batch size	Loss	Optimizer	Training Device
1e-4	16	CrossEntropy	Adaptive Moment Estimation (ADAM)	2 NVIDIA GeForce RTX 4090

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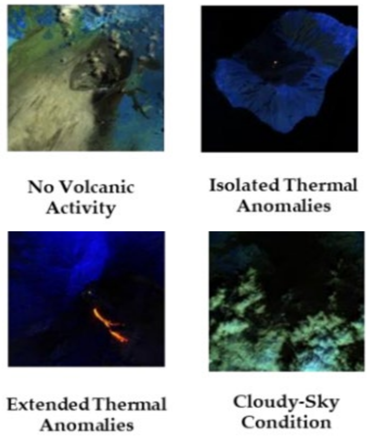

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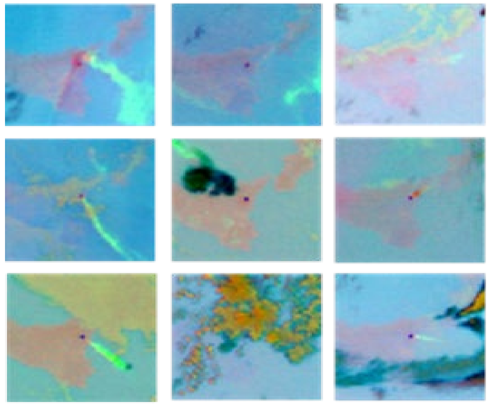

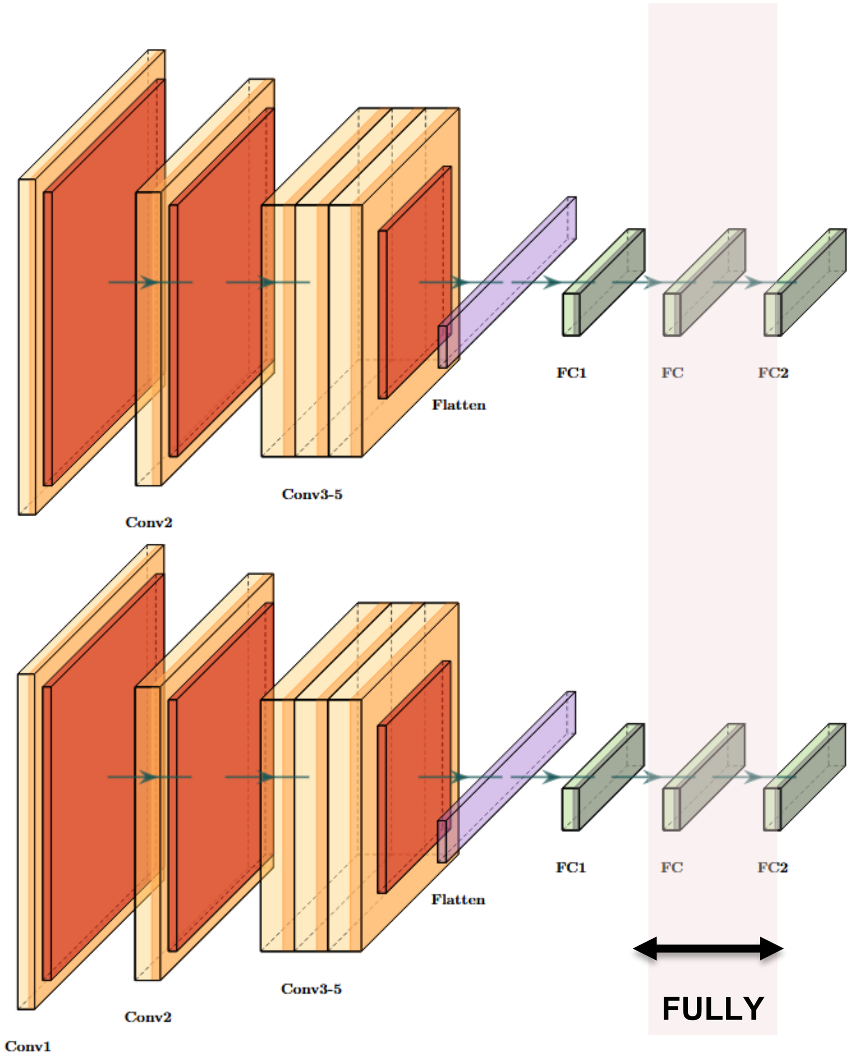

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RESULTS

Parameter-to-Performance Efficency → Data Scaling Analysis → Resilience to geometric changes → Convergence time

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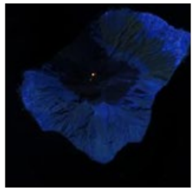
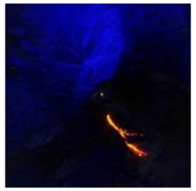
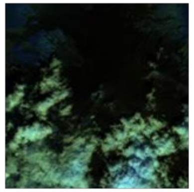
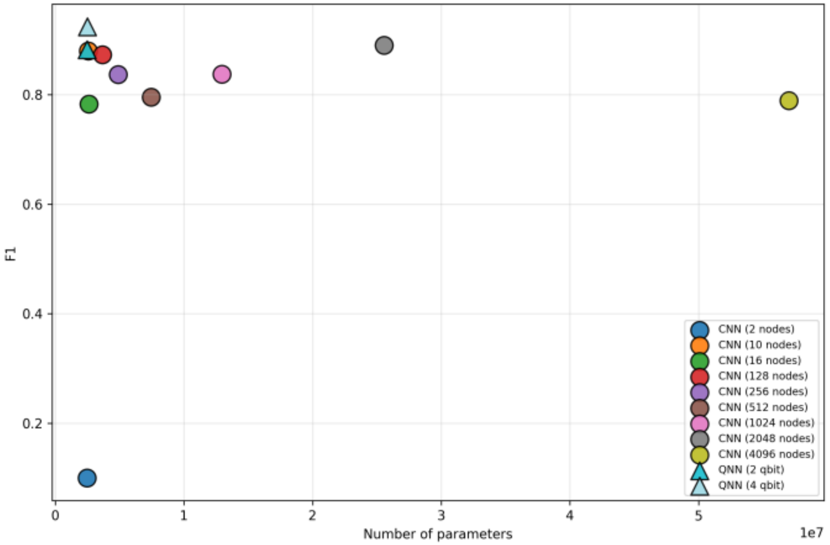
No Volcanic Activity


Isolated Thermal Anomalies


Extended Thermal Anomalies


Cloudy-Sky Condition



$$\epsilon_{ideal} = \frac{1}{P_{min}} \tag{4.1}$$

The *Relative Efficiency* (ϵ_{rel}) is then calculated for each model as the ratio between its actual efficiency and the ideal reference. This scales the results such that a model with minimum parameters and a perfect F1-score (1.0) would represent the 100% efficiency benchmark:

$$\epsilon_{rel} = \frac{F1\_score/P_{model}}{\epsilon_{ideal}} = F1\_score \cdot \frac{P_{min}}{P_{model}} \tag{4.2}$$

Table 4.4: Complete Normalized Parameter-to-Performance Efficiency (ϵ_{rel}) relative to the ideal density benchmark ($P_{min} = 2,488,148$), ordered by efficiency.

Model	Parameters	Overall F1	Rel. Efficiency (ϵ_{rel})
Ideal Benchmark	*2,488,148*	*1.0000*	*1.000*
QNN (4 qubit)	2,506,600	0.9241	**0.917**
QNN (2 qubit)	2,488,150	0.8819	**0.882**
CNN (10 nodes)	2,562,020	0.8801	0.855
CNN (16 nodes)	2,617,508	0.7830	0.744
CNN (128 nodes)	3,666,500	0.8730	0.592
CNN (256 nodes)	4,896,068	0.8369	0.425
CNN (512 nodes)	7,453,508	0.7954	0.265
CNN (1024 nodes)	12,961,604	0.8374	0.161
CNN (2048 nodes)	25,550,660	0.8902	0.087
CNN (2 nodes)	2,488,148	0.1000	0.100
CNN (4096 nodes)	57,020,228	0.7889	0.034

RESULTS

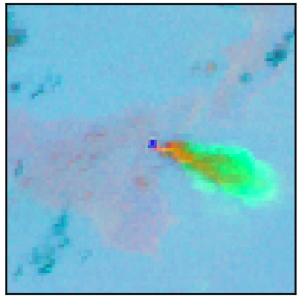
Rapidly evolving volcanic phenomena: Volcanic Clouds Classification using HTR

Parameter-to-Performance Efficency → Data Scaling Analysis → Resilience to geometric changes → Convergence time

SEVIRI Ash RGB image
08-07-2024 07:42
Class: Background

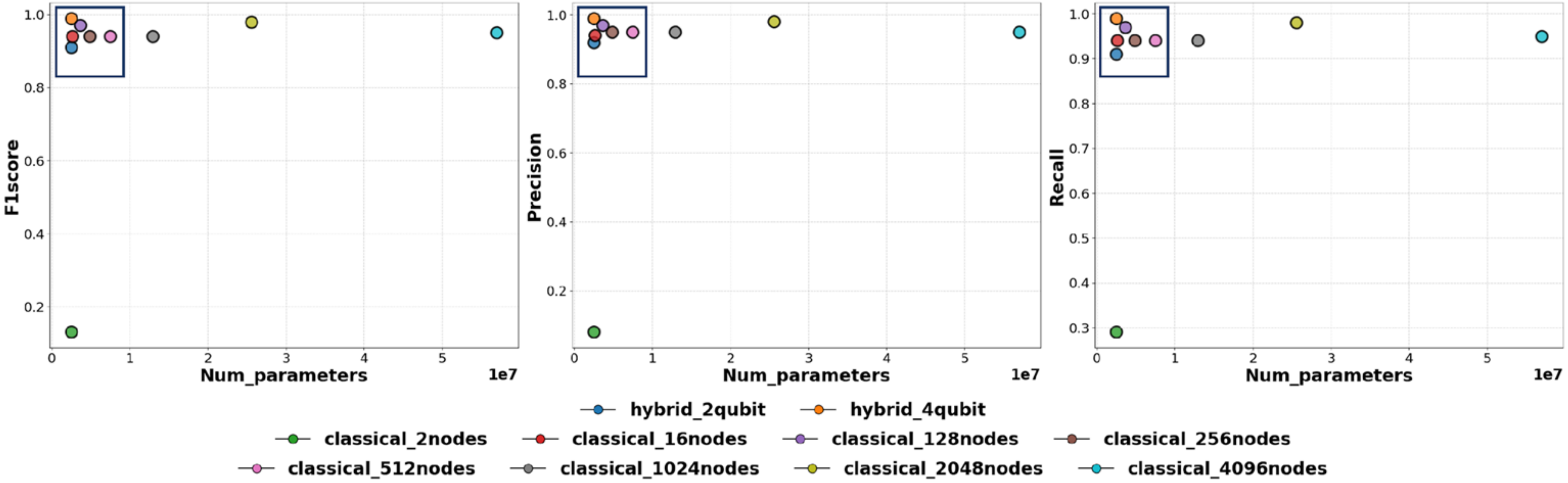
SEVIRI Ash RGB image
07-03-2021 23:57
Class: Meteorological Clouds

SEVIRI Ash RGB image
09-08-2021 04:27
Class: VolcanicClouds



DATASET DIMENSION :
1000 images (350 for each class)

SPLITTING
(TRAINING/VALIDATION/TEST):
70%, 15% , 15%



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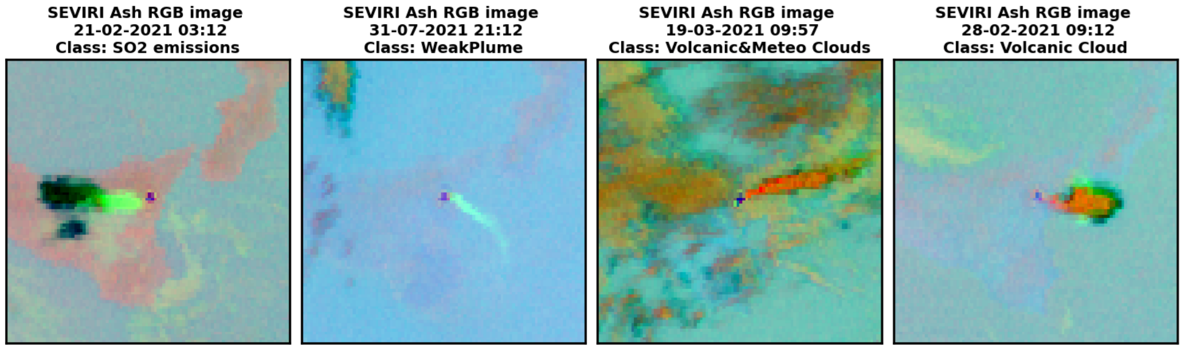

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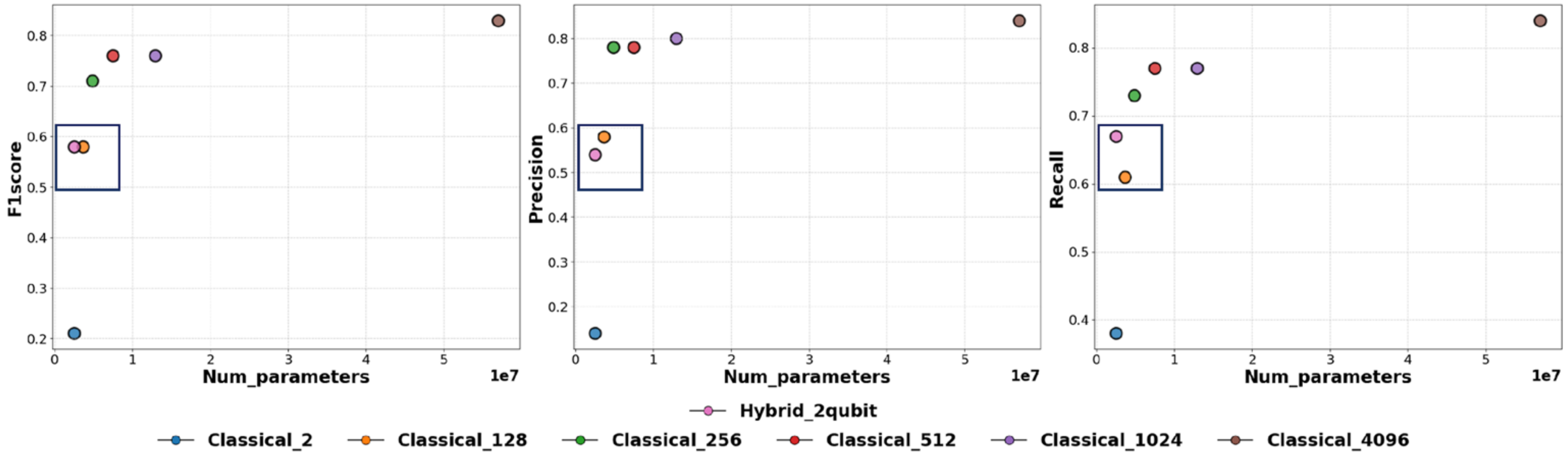


RESULTS

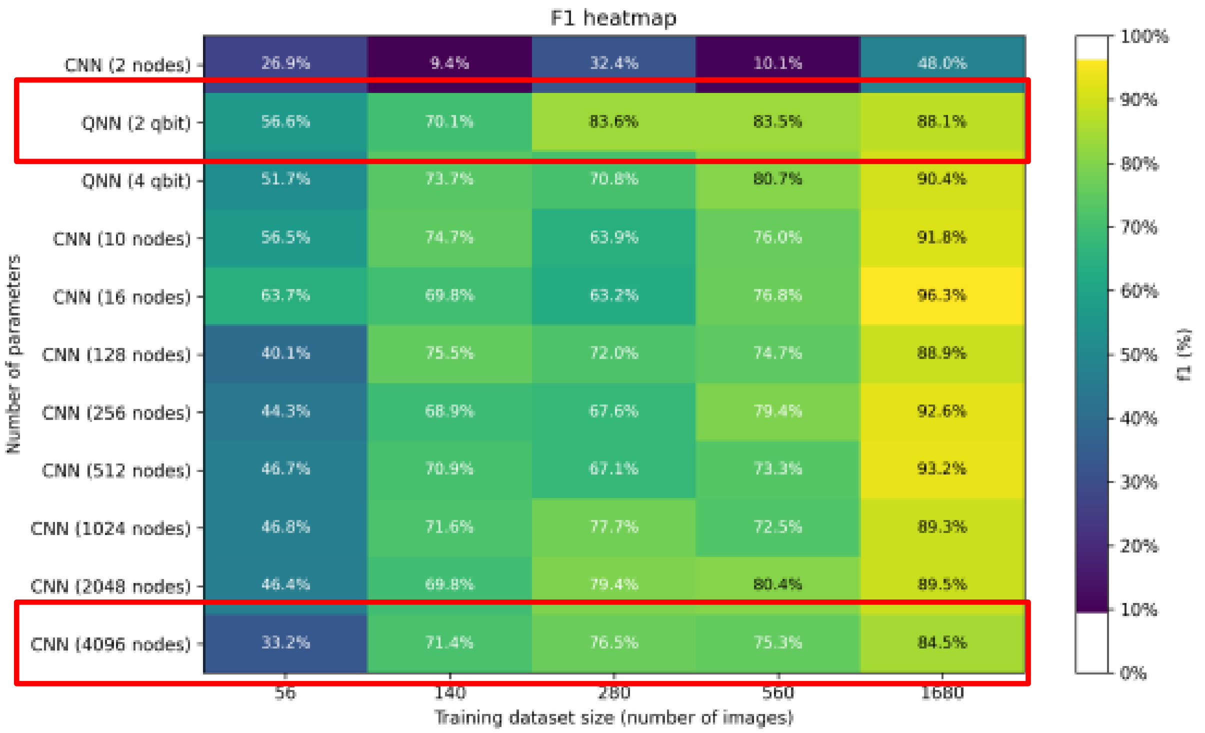
The QNN architectures demonstrate superior learning capability, particularly in regimes characterized by a scarcity of training samples.

Parameter-to-Performance Efficency | **Data Scaling Analysis** | Resilience to geometric changes | Convergence time

The **scalability** of the proposed models is evaluated by training both classical and quantum architectures on varying subsets of the original dataset.

The assessment of how models scale with the size of the training dataset provides critical insights into their underlying efficiency and practical utility for real-world volcanic monitoring.

How performances change with dataset size for each model



(a) F1-score Heatmap: Analysis of model stability and scaling.

RESULTS

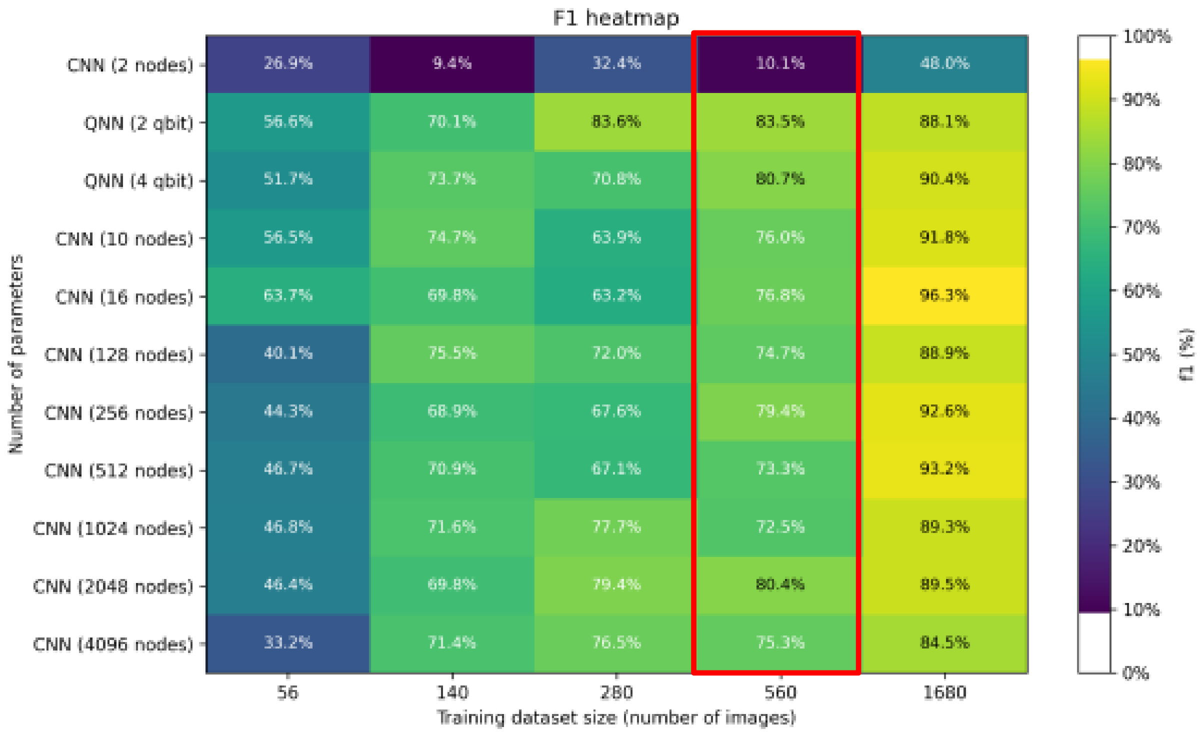
QNN architectures demonstrate a more stable optimization landscape compared to oversized classical models.

Parameter-to-Performance Efficency → Data Scaling Analysis → **Resilience to geometric changes** → Convergence time

The model robustness to rotational invariance and increased geometric complexity was assessed.

QNN maintain a high-performance baseline, suggesting that mapping features into a high-dimensional Hilbert space provides a representation that is less sensitive to specific pixel orientations.

How performances change considering targets with different morphologies



(a) F1-score Heatmap: Analysis of model stability and scaling.

RESULTS

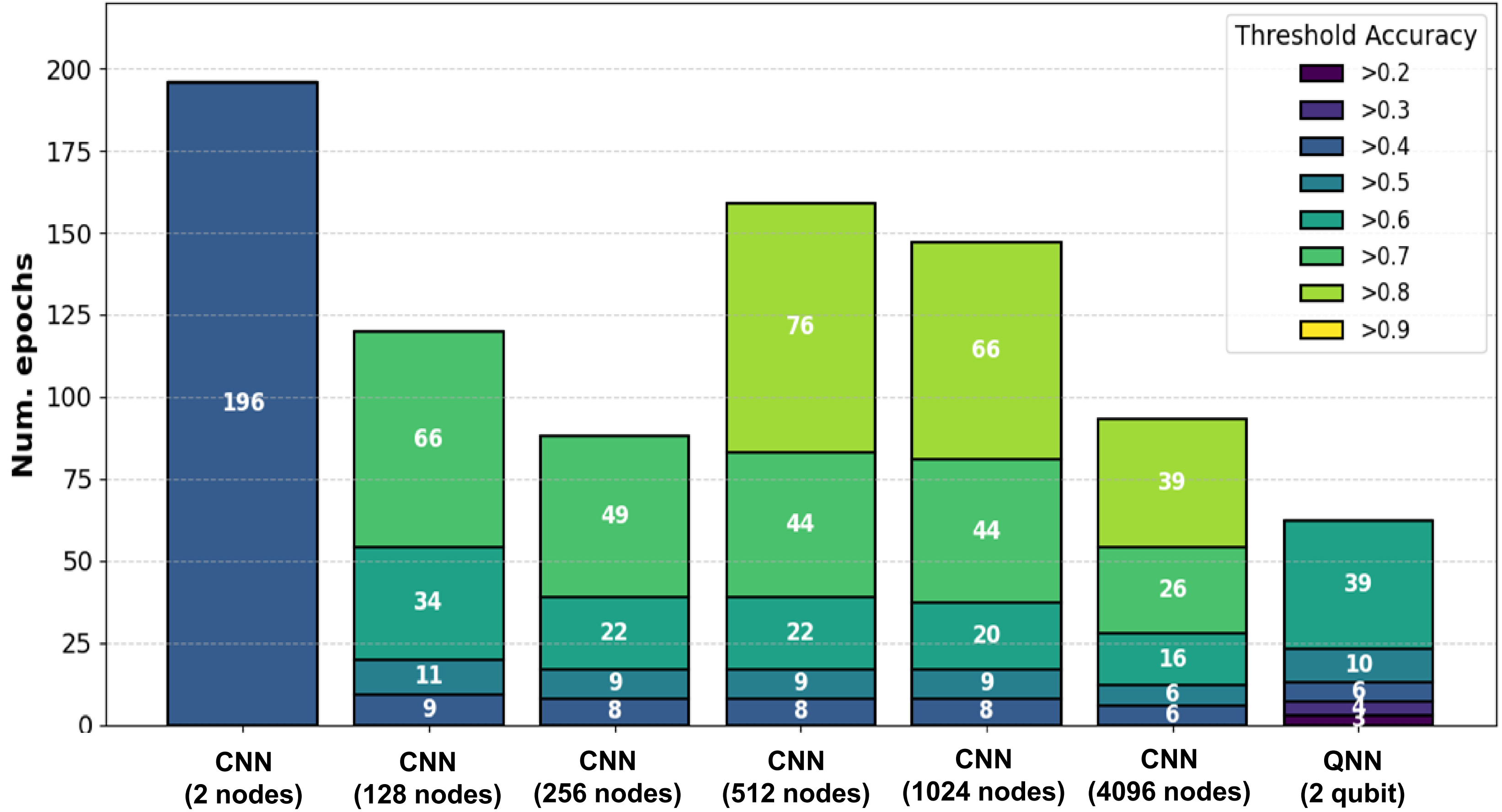
QNN converges faster, requiring significantly fewer iterations to reach optimal accuracy than classical models.

Parameter-to-Performance Efficency

Data Scaling Analysis

Resilience to geometric changes

Convergence time



CONCLUSIONS

This work demonstrates the distinct advantages of employing hybrid QNNs for volcanic monitoring .

- **Parameter-to-Performance Efficiency**: The empirical evidence highlights that QNNs leverage quantum dimensionality to maintain high reliability with significantly fewer computational resources than classical counterparts.
- **Sample Efficiency and Data Scaling**: A key finding is the exceptional resilience of quantum architectures in small-data regimes. This has profound implication for satellite monitoring in remote volcanic areas, where labeled data is often scarce, expensive to obtain, or heavily imbalanced.
- **Geometric Robustness:** Although absolute metrics were influenced by geometric transformations in the test set, the consistent lead maintained by QNN architectures proves their superior resilience to orientation and morphological changes.
- **Convergence time**: it chieves faster convergence by utilizing the high-dimensional feature mapping of qubits, allowing the model to reach optimal accuracy with significantly fewer training iterations.

FUTURE WORKS: the limitations identified in classical feature extraction suggest a natural evolution toward **Quanvolutional Neural Networks.**

THANKS FOR YOUR ATTENTION

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