Hybrid Classical-Quantum Neural Network for Improving Space Weather Detection and Early Warning Alerts

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Outline

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Introduction: Quantum Computing

- Quantum computing is an emerging technology that aims to speed up and enhance the performance of classical computing in different areas, including machine learning, cybersecurity, and more [1].
- The basic idea is that quantum computers utilize qubits to speed up and strengthen data processing.

Introduction: Solar Flares and Geomagnetic Storms

- Solar flares and geomagnetic storms impact space technologies and infrastructure.
- Disruptions in communication systems, power grids, and satellite operations [2, 3, 4].
- Solar radiation is a crucial component of space weather.
- Solar flares and geomagnetic storms caused by release of solar radiation [2, 5].

Introduction: Importance of Predicting Solar Radiation

- Predicting solar radiation enables early warning alerts Identifies patterns and trends in solar activity.
- Helps issue early warnings to space agencies and critical systems operators [6, 7].
- Precautions can be taken to protect astronauts, satellites, and stabilize power grids.

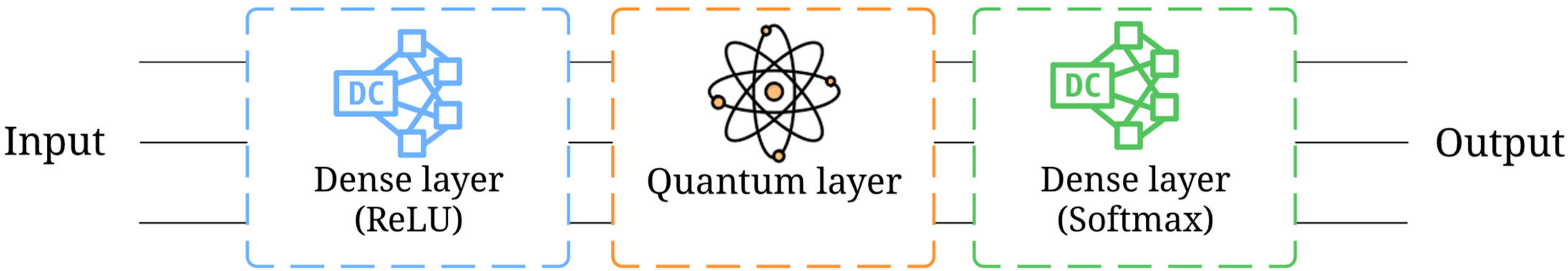
Introduction: Traditional Methods Limitations

- Traditional methods for detecting and forecasting space weather reliance on statistical models and empirical data analysis.
- Limited accuracy and speed [6, 8, 9, 10, 11] Potential disruptions and damage to critical infrastructure.

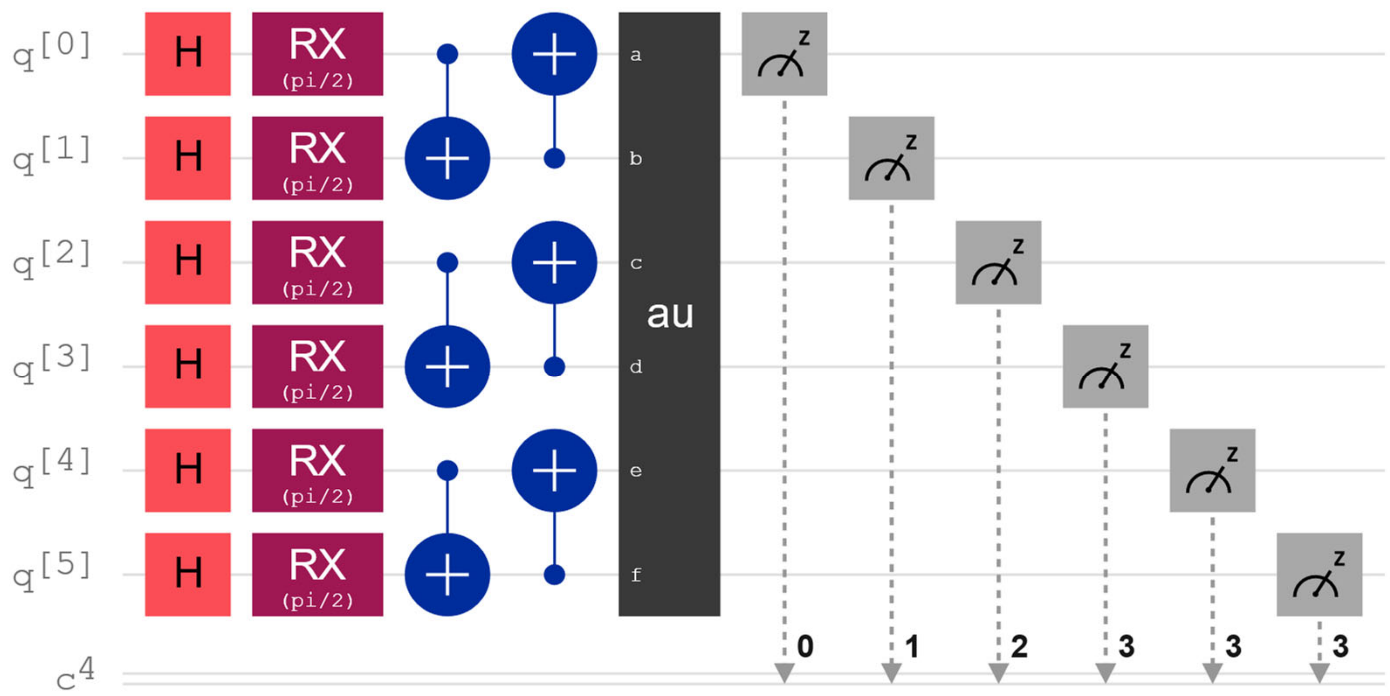
Research Objective

- The goal of the proposed HCQNN is to Integrate superposition, nonlinear entanglement, and quantum activation functions with classical NN to enhance the detection of geomagnetic storms by analyzing space weather, including solar radiation.

The Proposed HCQNN



The Quantum Layer: The Variational Quantum Circuit (VQC)



The Quantum Layer Components

- Superposition: The H gates.
- Encoding: The angle embedding encoding technique [12, 13] using the Rx gates.
- Entanglement layer: The CNOT gates.

The Quantum Layer Components

- Quantum activation function $au(\theta, \phi, \lambda)$: Represents the unitary transformation of the entangled quantum states [14, 15].
- $|\phi\rangle = \frac{1}{\|\phi\|} \sum_{i=0}^{n} \phi \big| q_i \rangle \in C^2.$
- $|\lambda\rangle = \frac{1}{\|\lambda\|} \sum_{i=0}^{n} \lambda \big| q_i \rangle \in C^2.$
- Measurements: Measures and collapses the entangled quantum states into classical data to be fed to the last dense layer to perform the classification.

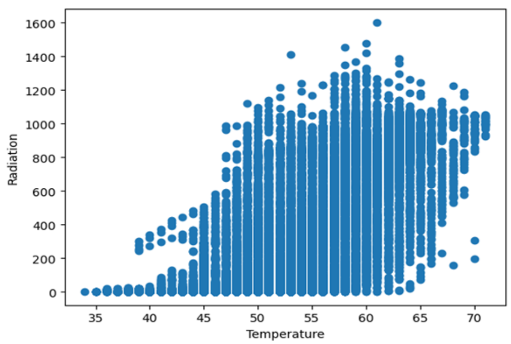
Experiments and Results: Dataset

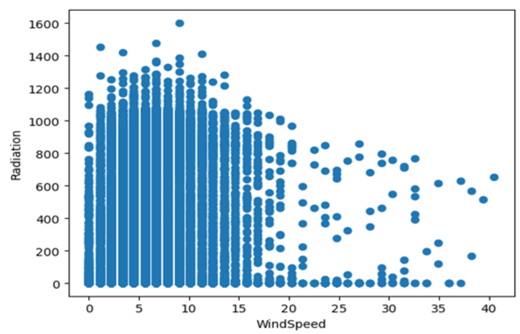
- To evaluate the performance of the HCQNN, we tested it using a solar radiation space weather dataset generated from the Hawai‘i Space Exploration Analog and Simulation (HI-SEAS) station [16].
- The dataset contains 32687 samples and 10 features.

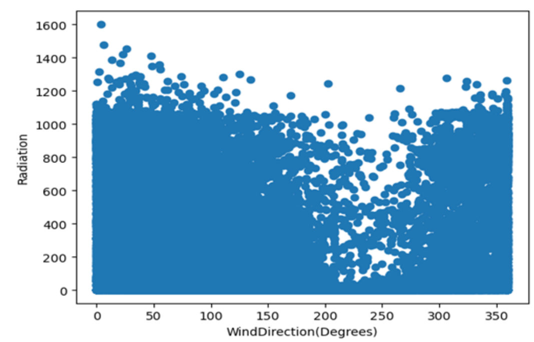
Experiments and Results: Preprocessing

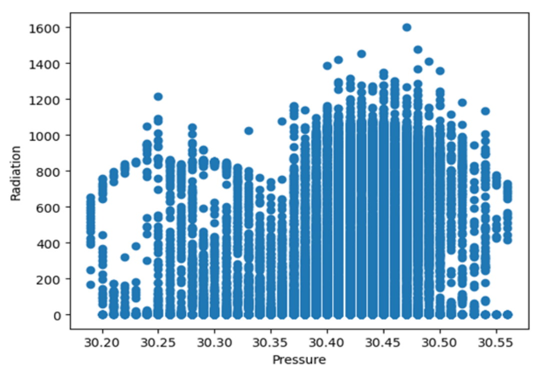
- To make the dataset suitable to detect geomagnetic storms:
- We studied the relationship between solar radiation and each other. features in the dataset.
- We found that pressure, humidity, wind speed, and direction exhibited the most significant correlations with solar radiation.

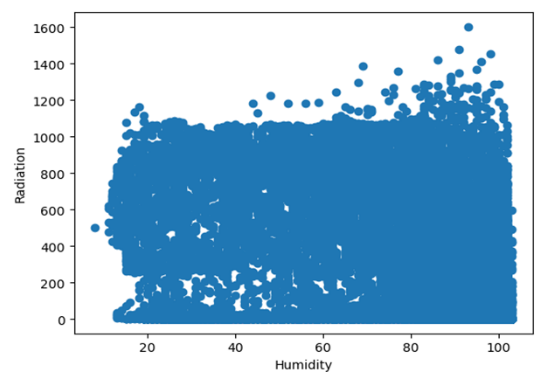
Experiments and Results: Preprocessing











Experiments and Results: Preprocessing

- Solar radiation is measured using Solar Flux Unit (SFU) and one $SFU = 10^{-22}\ W/m\hat{}2$ [17].
- Geomagnetic storms occur when solar radiation reaches or exceeds 10 SFU [2, 5].
- We added a new column called "label“, which assigns a specific label of GeomagneticStorm or NoStorm to each sample based on the solar radiation level.
- For example, a sample that has solar radiation ≥10 is labeled as GeomagneticStorm.
- After labeling each sample, we standardized and normalized the dataset.

Experiments and Results: Setup

Elements	Value	Description
Packaged used	Pennylane, Qiskit tensorflow, keras, numpy, matplotlib, mpl_toolkits, sklearn, and pandas	All the classical and quantum packages that are used to process the proposed HCQNN approach
Training dataset size	818	The size of the training dataset to learn the HCQNN model
Testing dataset size	246	The size of the testing dataset to test the HCQNN model
Features	6	Number of the features in the dataset
Batch size	5	The number of samples that will be propagated and passed through the HCQNN at one time.
Epochs	10-100	Number of times to run the quantum circuits of the HCQNN and benchmark models to generate the measurements results
Qubits	6	Number of qubits used to process the dataset
Quantum simulator	default.qubit	Pennylane quantum circuit simulation
IBM quantum computer service provider	ibm-q	The provider of the IBM quantum service that allows the execution of the NLQNN on the backend that runs the quantum computer
Backend	ibm_oslo	7-qubit IBM quantum computer

Experiments and Results: Results

Epochs	Approach	Accuracy %	Recall	Precision	F-score	Error rate	Wall time in minutes
10	HCQNN	98.079	98.14	98.015	98.421	1.92	14
	LHCQNN	82.146	84.784	85.95	82.673	17.8	16.4
20	HCQNN	98.126	98.241	98.111	98.512	1.92	22
	LHCQNN	82.146	84.784	85.95	82.673	17.8	24
30	HCQNN	98.211	98.256	98.170	98.579	1.8	35.9
	LHCQNN	82.146	84.784	85.95	82.673	17.8	37.9
40	HCQNN	98.251	98.289	98.211	98.598	1.75	46
	LHCQNN	82.146	84.784	85.95	82.673	17.8	50
50	HCQNN	98.455	98.469	98.242	98.624	1.545	56.92
	LHCQNN	82.146	84.784	85.95	82.673	17.8	59.55
60	HCQNN	98.461	98.577	98.276	98.704	1.541	67.25
	LHCQNN	82.146	84.784	85.95	82.673	17.8	69.30
70	HCQNN	99.650	99.241	98.970	99.732	0.35	82
	LHCQNN	82.146	84.784	85.95	82.673	17.8	90.9
80	HCQNN	99.702	99.422	99.121	99.810	0.35	95.8
	LHCQNN	82.146	84.784	85.95	82.673	17.8	97
90	HCQNN	99.741	99.624	99.526	99.885	0.259	111
	LHCQNN	82.146	84.784	85.95	82.673	17.8	113.91
100	HCQNN	99.921	99.928	99.751	99.921	0.079	126
	LHCQNN	82.146	84.784	85.951	82.673	17.8	138

Conclusion

- Proposed a HCQNN that integrates superposition, entanglement, and quantum activation function for enhancing the detection geomagnetic storms.
- Compared the HCQNN with a classical NN, HCQNN outperformed with better performance results.
- The results indicts that the HCQNN, is an effective strategies for mitigating space weather impacts on technological infrastructure.

Future Work

- Adding more quantum layers to the proposed HCQNN.
- Applying it to more complex and larger datasets.

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