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Storm Chasing Using Quantum Machine Learning

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Abstract

A vast amount of images generated from high resolution telescopes, satellites, on the ground cameras and other sources are processed daily to get various insights affecting economy, business, individual lives. This necessitates ability to store huge amount of data. During image processing different techniques are involved future recognition ,classification problems which belongs to supervised learning. This may not be provided using classical computation. Here quantum computing can be useful due to its ability to process huge amount of data. This Project aims to leverage current Noisy Intermediate Scale Quantum(NISQ) devices to deploy classical, hybrid and quantum inspired algorithms such as Grover algorithm, Quantum Neural Network(QNN) to model Storm chaser-relevant data points and deliver more accurate medium-term and medium-scale prediction of storm.

Keywords: Quantum Computing, Grover algorithm, QNN.

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1. Introduction

Storm-mode classification is an important task for both real-time weather forecasting and climatological analysis. As the National Weather Service builds next-generation forecast systems for that make use of automated technology [e.g.,probabilistic hazard information, discussedin Gallo et al. (2017)and Rothfusz et al. (2018)], a real time system that classifies storm-mode can help guide automated warnings, since storm-mode is correlated with hazards such as hail and tornadoes (Smith et al. 2012; Thompson et al. 2012).In addition, accurate and automated storm- mode classification would allow for long-term climatologies. These climatologies could answer questions such as "how oftendo super cells occur at my location?" or "what is the most common convective mode at my location?" These questions could also be broken down by time of day, time ofyear, synoptic régime, etc. Furthermore, we could study trends in convective mode as a functionof climate change or internal climate variability.

2. Software used

2.1. Pennylane

PennyLane is an open-source software framework for quantum machine learning, quantum chemistry, and quantum computing, with the ability to run on all hardware.It is the leading tool for programming quantum computers.It is a cross-platform Python library, it enables a new paradigm — quantum differentiable programming — that enables seamless integration with machine learning tools.

2.2. Qisikit

Qiskit is an open-source software development kit for working with quantum computers at the level of circuits, pulses, and algorithms. It provides tools for creating and manipulating quantum programs and running them on prototype quantum devices on IBM Quantum Experience or on simulators on a local computer. It provides a set of tools for composing quantum programs at the level of circuits and pulses, optimizing them for the constraints of a particular physical quantum processor, and managing the batched execution of experiments on remote-access backend.

3. Architecture

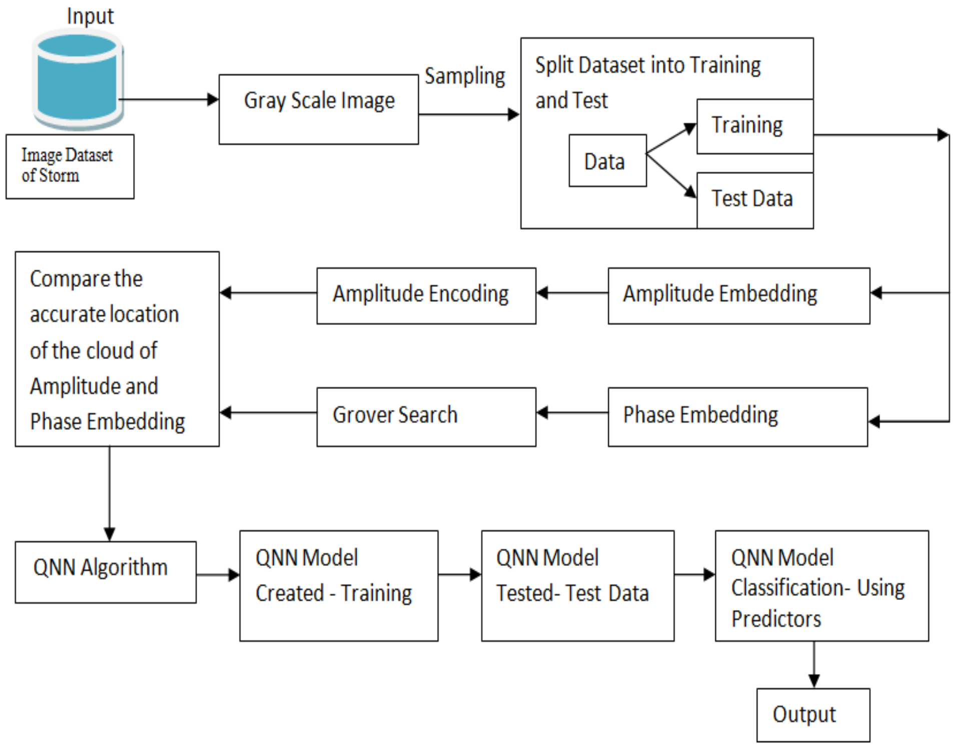

Figure 1. Architecture of Quantum Machine Learning

3.1. Datasets

The dataset will be used as training the dataset for the training of our model. We collected original image dataset for our project. The comments in dataset cannot be directly fed intothe modelsconstructed.

3.2. Embedding Process

Encoding the classical data into quantum circuits is an important step as we move toward quantum machine learning applications. Our team is interested in embedding the weather datafor quantum computers. There are many ways to encode the data [1,2], we started with the simple amplitude encoding, |ψ⟩ = , where is the classical data, and N is the total i=1 N ∑ x i |i⟩ x i number of the data we are interested in encoding. Images can also be mapped into quantumstate by taking 2D data into 1D data. There is a proposal to embed the RGB data [1], but for simplicity, we encoded the black and white data into quantum state

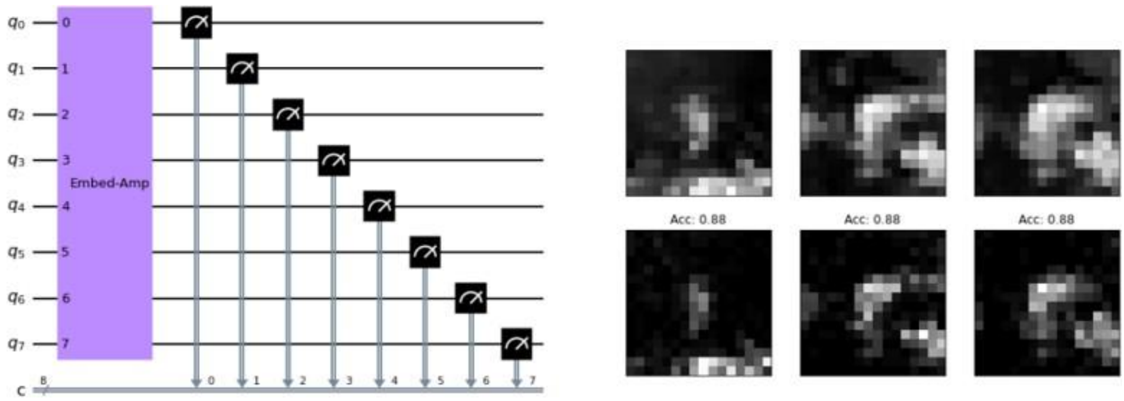

Figure 2. Amplitude Encoding

We used the qiskit initialize function to embed the classical dataset. In Fig.2, simple embeddingof amplitude is presented. On the right side of the figure, top images are the original data of satellite image of storm [2], and the bottom images are the result of the amplitude encoding. We measure the state and reconstruct the image by looking at the probability distribution. Thereis overall good accuracy (more than 85%) between original data and the result of the amplitude encoding.

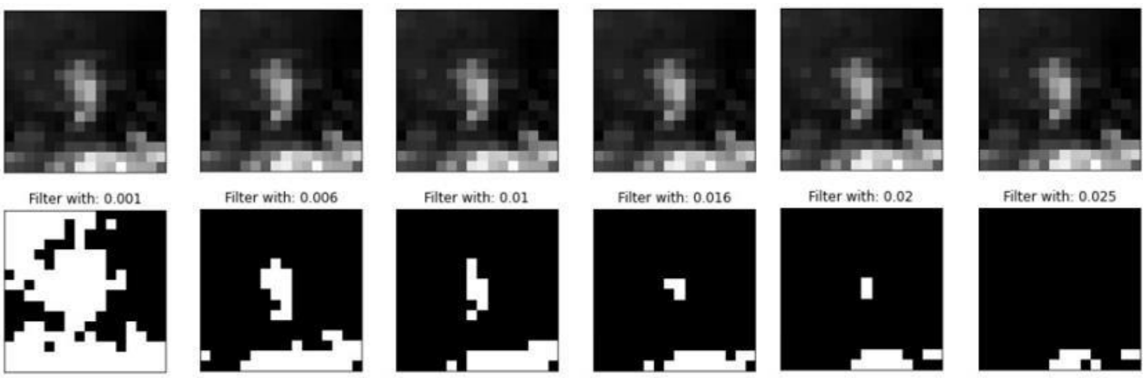

Figure 3 Filtering the image

As we are using the probability distribution, amplitude encoding can be used as an easy implementation of image contrast. By reducing the size of the number of the shots or thresholdof pixel value of the image, we can binarize the image. As shown in Figure 3, we increase thethreshold from 1 shot to 25 shots out of 1000 shots. This allows us to detect the regions of the clouds.

Phase Embedding Another interesting way to encode the data is in the phase of the superposition state, |ψ⟩ = . In this task, we create the unitary matrix by generating the diagonal i=1 N ∑ 1/ N exp(i x i)|i⟩ matrix, and transform the unitary matrix into a gate by unitary function. By phase embedding the classifical information, we provide another interesting application by integrating the grover search algorithm.

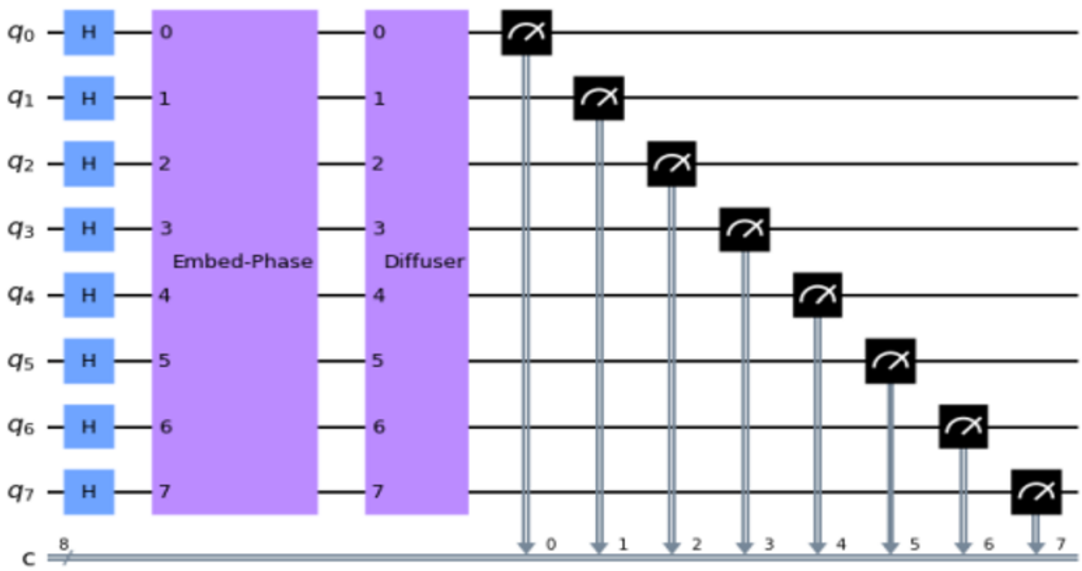

Figure 4. Grover search

Grover search algorithm is the quantum algorithm which shows quadratic speed up forunstructured searching with high probability of finding particular input value. Typically, grover search requires π/(4 N) iteration, which is in this case ~12.5 iteration. However, as we can see in the original image, we have many bright location more than >7, so iteration is closeto π/(4 N/k) = 4. 7where k is the number of the unique data we are interested in. As we have quadratic speedup for the searching algorithm, this method can be applied to the data acquisition in the space where they have limited storage and resources.

3.3. Evaluation QNN

As we have quadratic speedup for the searching algorithm, this method can be applied to thedata acquisition in the space where they have limited storage and resources. network (QNN).Figure 6 (right) shows the typical work flows for classical neural networks. In typical machine learning, data is inserted to the neural network, calculates the loss function, and the hidden layer is optimized. On the other hand, the quantum neural network, parameterized quantum circuit is optimized instead of optimizing the hidden layer

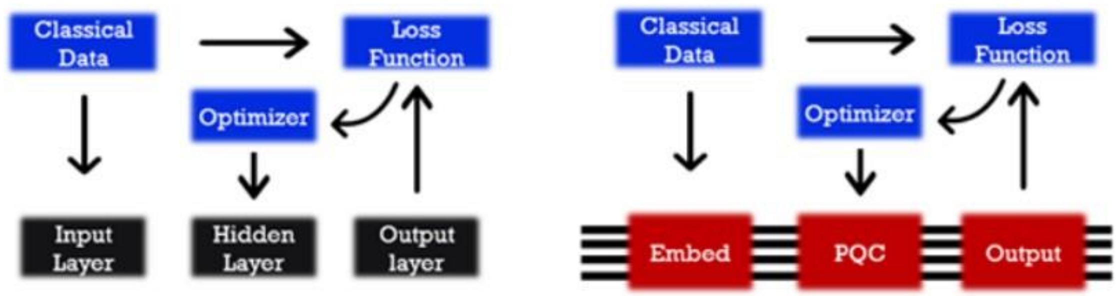

Figure 5. Workflow of classical and neural network

3.4. Parameterized quantum circuit

We embed the data using parameterized quantum circuit (PQC) shown in Ref [5]. In this paper, they define the expressibility of each circuit where expressibility is the measure of how the circuit is expressible in the Hibert space. In particular, we choose circuit 15 where it shows good expressibility and entanglement capability. We use this PQC for both encoding and optimizing the hidden layer of the parameterized quantum circuit. For encoding the dataset, we had to repeat the PQC over 6 times to have 72 (6*2*7) possible location for encoding the data. Our 8x8 pixel is encoded into the 72 parameters, and the last 6 (72-64) parameters are set to equal to pi. For the training purpose, we load 15 images for encoding the dataset.

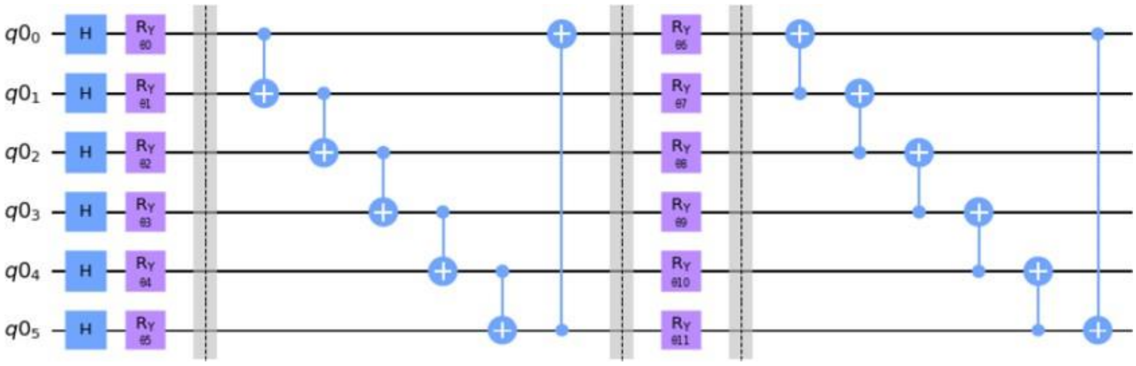

Figure 6 PQC

Figure 6 is the example of the stormy data vs no-storm data. We would like to know by training QNN that given image has “storm” or “no storm.” As we decrease the size of the image, it is hard to see if there is strom or not, but it is still possible to tell if there are lots of clouds or not. We are not really sure how QNN decides if the image is storm or not, it is possibility that QNN classify the result by overall brightness of the image.

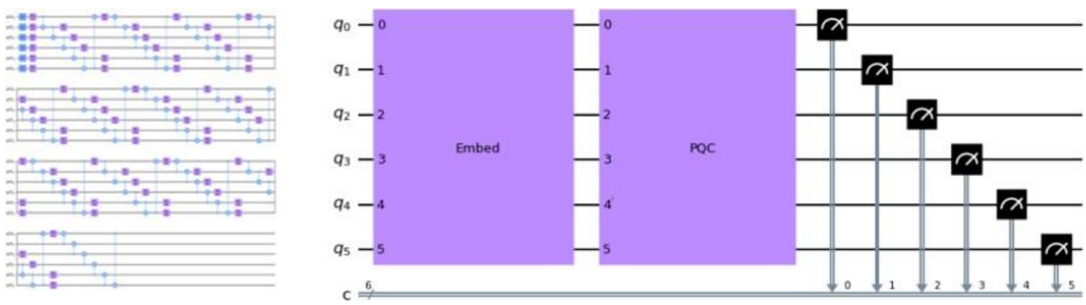

Figure 7 Encoding structure and QNN Structure

So, first we encode our image into an embedding circuit, pass through the PQC, and measure the bit string. Final bitstring is a map to classify the “storm” or “no storm.” We used the mapping method provided by Ref [6] where the first and last quarter of the bitstring is mapped to 0 (|000000⟩,|000001⟩,|000010⟩….) and the rest of the bitstring is mapped to 1 (|010000⟩,|010001⟩, |010010⟩). By using CircuitQNN, we can connect the Torch module and optimize the parameterized circuit. LBFGS optimizer and CrossEntropyLoss is used to optimize the result.

4. Result

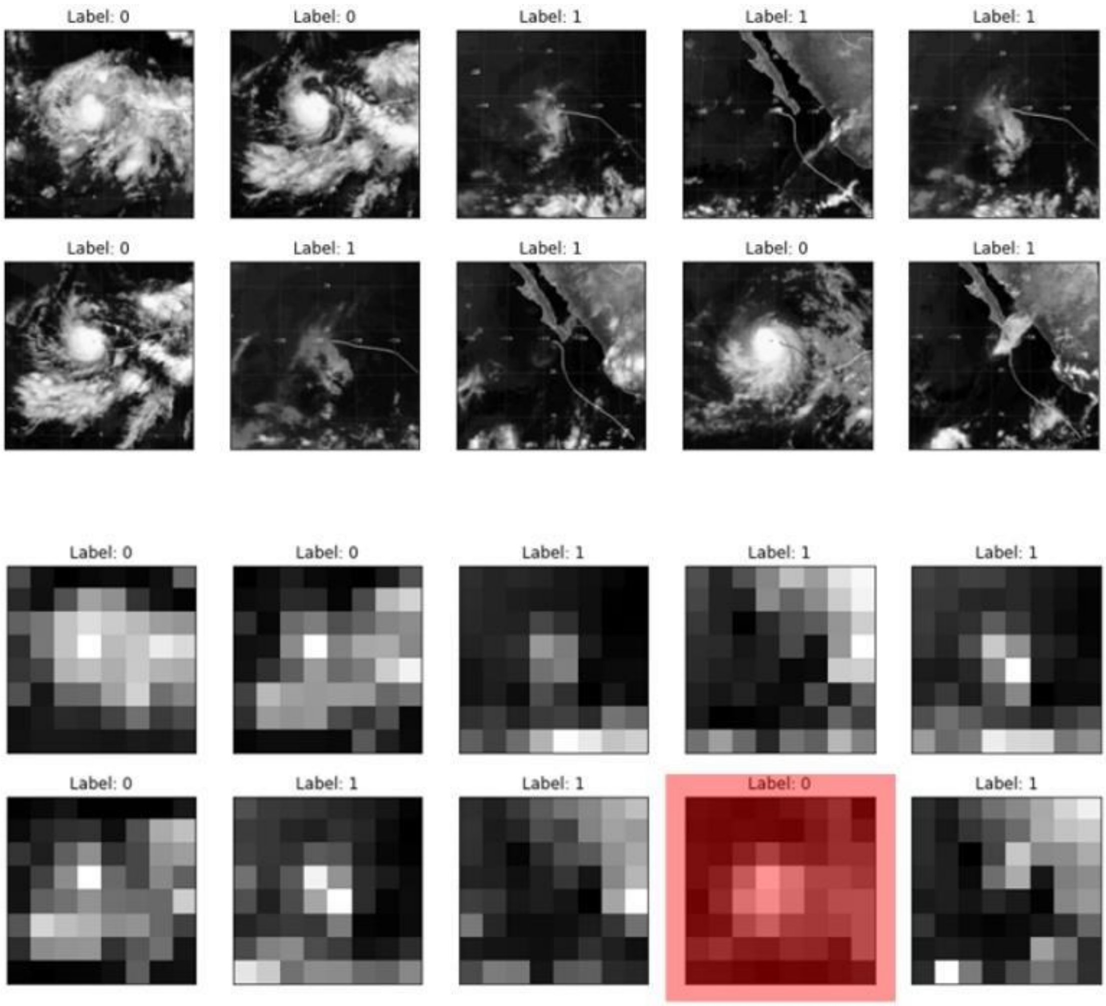

Figure 8 Classification Result

Figure 8 shows our result from verification data. For red marked data, is where we havefailed to classify, but the rest of the data is correctly classified.

6. Conclusion

Figure 8 shows our result from verification data. For red marked data, is where we have failed to classify, but the rest of the data is correctly classified!

Training (15 images)	**Verifying (10 images)**
86%	90%

Results are very promising that we can successfully train the data with high accuracy. Our future work, we will apply quantum-inspired and hybrid quantum-classical algorithm on real-world data to compare its performance.

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