Understanding Amazon Basin Deforestation using Computer Vision

Mansi Patel Prajakta Narsay Yashwanth Saladi
University of Maryland Baltimore County
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Abstract- Amazon is one of the largest forests in the world and is home to many species of flora and fauna. But increase in civilization has increased deforestation in the Amazon rainforest. So, the local authorities need to understand the amazon rainforest to counter deforestation. Manually checking the land cover of the forest for surveillance is not a feasible option. So, classifying the satellite images of different regions in the Amazon to understand what activities causes deforestation may help many stakeholders like government authorities, NGOs, and environmentalists to take suitable actions and tackle deforestation. These satellite images can be classified into 17 different labels identifying different activities in the rainforest. In this project, we will build a hybrid model of Quantum Convolutional Neural Networks and Classical Neural Networks to classify satellite images.

1. INTRODUCTION

Deep Learning algorithms today can do many tasks based on Supervised learning, Unsupervised learning, and Reinforcement learning. Supervised learning can be used for classification of images into various classes. This is one of the major tasks in computer vision. Classification helps machines to understand and learn how images of a particular type look like. Combination of various image processing algorithms and Deep learning computing techniques constitute Classical Machine learning. By 'classical' it means, the algorithm and the underlying hardware both are classical in nature. The other way to perform it is using some non-classical techniques like Quantum computing.

Quantum Computing is an evolving field and has applications ranging from classical physics, computation and even machine learning. Google and IBM have Quantum Computers today. TensorFlow launched TensorFlow quantum in May 2020 which is capable of organizing and simulating quantum circuits. This quantum circuit acts as a model which is similar to the neural network in machine learning. There are many similarities and differences between the classical machine learning and Quantum Machine learning which will be discussed in the later section in the report. The approach in this report uses Quantum Machine Learning that represents labelled data and can be trained using Supervised learning.

A quantum circuit requires quantum data and therefore one of the major aspects of this project was to quantize the classical data. The images in figure 1, are samples from the dataset which initially had three channels that are Red, Blue, and Green. Therefore, the size of any sample in the dataset was a matrix of (512,512,3). Further while using the quantum circuit, this dataset was quantized and then passed into the model for processing. The approach presented in this report shows how the combination of classical machine learning techniques and quantum computing techniques can be used in a hybrid way to classify the satellite images of the Amazon rainforest.

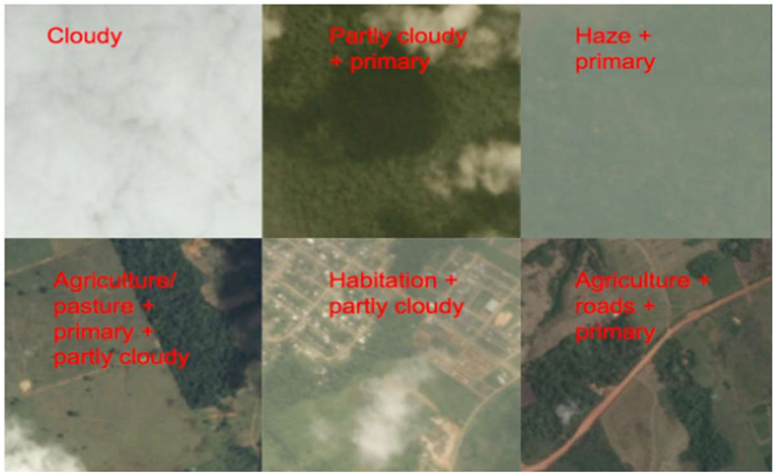

Figure 1. Dataset

2. RELATED WORK

This section of the report specifies the related work in detail. The classification technique related to this report is based on the satellite images of the Amazon basin. Satellite images are mostly of higher resolution and hence larger in size. To process such high-resolution images such that no more information is lost, data pre-processing is a major step. Combining the techniques from classical convolutional neural networks and quantum convolutional neural networks can help us in better understanding the approach to classify satellite image of Amazon Rainforest.

'The Planet: Understanding the Amazon Rainforest from space' was completed in the year 2017 and the winners classified the test data with 93.3% and believed to use different ensemble models. Also, single model without using any ensemble models can achieve 90% of an accuracy on the test set. (Bragilevsky & Bajić, 2017) depicts the approach to achieve 93% accuracy with ensemble models and how fully connected layers using CNN works for classifying satellite images. In reference (Farooq rt al., 2017) & (Tun & Gavrilov, 2020), authors have discussed many architectures and pre-trained models like Deep CNN architectures for multi class classification. In (Tun & Gavrilov, 2020), it was concluded that GoogleNet and Alexnet work perfectly for multiclass classification. Reference (Jog & Dixit, 2016) explained the methods of processing images for multiclass classification. It was observed that all pretrained models were being used and these all approaches belonged to the classical Neural Networks. (Cong et al., 2019) and (Seunghyeok et al., 2020), implemented QCNN for image classification. This report proposes Quantum Machine learning for multi label classification which is the novelty since we will be merging quantum and classical methods to classify data.

3. METHODOLOGY

For the problem statement we proposed, we want to introduce Quantum Machine Learning. Quantum Machine Learning can be done in three different ways by using:

1. Quantum Data and Classical Computing
2. Classical Data and Quantum Computing
3. Quantum Data and Quantum Computing

At present, it's difficult to have a Quantum Computer, which means it is not feasible and affordable. But, it's possible to simulate Quantum circuits on classical computers using Quantum data and Classical computing. In this process, the way of doing Quantum machine learning is to quantize the classic data, which means in order to solve the problem statement we need to convert image pixels into qubits.

The input to the model is quantum data which relies on the properties of quantum mechanisms like quantum superposition and quantum entanglement. As mentioned before, all pixels of an image are converted to qubits. All qubits are prepared in zero state. The weights in the classical neural networks correspond to Unitaries in Quantum Neural Network. Unitary is basically a linear operator whose inverse is its own adjoint. We need to tensor out the qubits of the next layer in the current state and then apply unitaries. The uniteries are represented as U^i_j ; where, i: previous layer for qubits and j : next layer. The training process consists of learning unknown unitaries 'V'. The training data is in the form of N pairs for $|\Theta_x >$, $V| \Theta_x >$; where $|\Theta_x >$ represents input state and $V| \Theta_x >$ represents output state. Output state is obtained by applying unitaries to input state.

Multiclass classification with 17 labels and 40,000 images in training was taking a lot of time to train the mode. Even using Google colab and its cloud-based resources, the problem of kernel crashing was irresistible. This made us club the labels from 17 to 5. This means we clubbed the forest as one class and all other related activities into other 4 classes. The total number of images used for training were still the same. But using this approach had the same problem as before. Using a lesser number of images in the dataset could not help us fight the issue. So, we decided to move from Multiclass classification problem to Binary Class classification problem. The approach in this report is purely based on classifying the images into Primary class (forest areas) and non-primary (activities like civilization, roads, mining, etc). The further aspects of implementation are discussed below.

The approach also used a quantum circuit to process qubits. It consists of a sequence of parameters which directly depend on the unitary transformation. These transformations act on the input states. The data sample in this approach is referred to as string which has a label assigned to it. Each string is made up of qubits. The unitaries act on the set of qubits and depend on a continuous parameter called 'Θ'. So, we have one controlled parameter per unitary. This parameter gets adjusted during learning such that measurement of the readout qubit after passing through the Pauli operator should produce the correct label for the input state. The output being in the quantum state is always not certain. The value of the label is between -1 to +1 which is actually an average of all the observed outcomes.

Just like the loss calculated in classical neural networks, there is a loss function used in Quantum machine learning as well. The loss function here, is defined based on parameters: Θ has the input string (z). The loss function is defined below

$$\text{loss}(\Theta, z) = 1 - l(z)\ \langle z,1|\ U(\Theta)\ Y_{n+1}\ U(\Theta)|z, 1\rangle$$

Where, Y_{n+1} is the readout qubit of the model which defines the label. U(Θ) is the set of unitary operations on the parameter 'Θ'. The loss function is the product of the true label and the predicted label. The loss function will be minimum at 0.

Figure 2 depicts model architecture used in our approach. Input state is shown by $|\Psi\rangle$. There are a total 17 qubits in one string where 16 qubits correspond to the converted pixels and 17th qubit refers to the readout qubit which is set to 1.

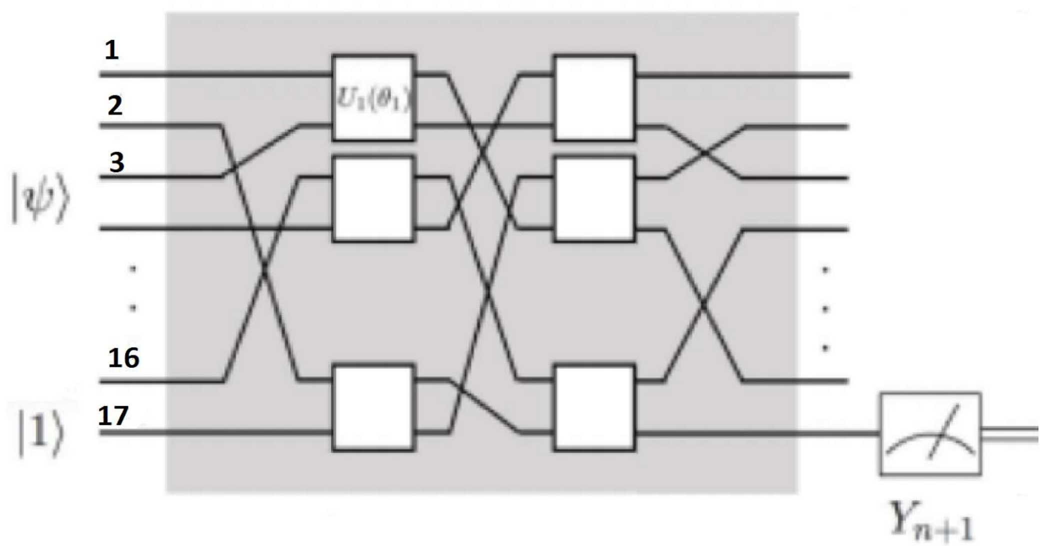

Figure 2. Model Architecture

We need to train the hybrid Quantum Neural Network in the same notion we train the classical networks. After passing the string to the model as input, pass the readout qubit to the Pauli operator. This gives a good estimate of Y_{n+1}. Upon completion of this, the loss is being computed which is dependent on the input string and parameter 'Θ'. Now, to increase the accuracy and reduce the loss, small changes in 'Θ' are made. This can be done by calculating gradient of loss (Θ, z) with respect to Θ. This gives a new and updated parameter 'Θ1'. We now take new string sample s2 and repeat the step described previously. Repetition is done until all the sample strings in the training data are processed. When learning is completed, the parameters settle into the place where labels are correctly predicted. In our case, the number of epochs for which the training was done is 5.

For our model, we are using a Hybrid model which is a combination of quantum convolutional neural networks and classical neural networks, and classical neural networks. The first layer of a hybrid model is a quantum convolutional neural network, which needs quantum data as input. But in our problem statement, we need to convert image pixels to quantum data. For this conversion, we need a cirq library. Cirq contains circuits that stimulate the transition gates which convert classical data to qubits. Classical qubits are nothing but quantum data.

4. RESULTS

We wanted to try QCNN, but we couldn't find any state-of-the-art implementation for supervised learning. And we faced issues in converting multi class labels to qubits. So, we changed our model from QCNN to QNN.

First, we tried to implement our model with 17 classes, the kernel used to die while training. So, we went with 5 class labels and we were not able to solve the kernel issue. At least we implemented binary class classification for our problem and our task is to classify whether the image has rainforest or not. We trained our model with balanced data and we are able achieve 59% accuracy. And we also observed that the accuracy increases when we increase our input strings, but we need to use imbalanced data or augmentation. We believe better accuracy will be achieved if we train our model with more numbers of strings which are pixels got converted into qubits.

Qualitative analysis

EPOCHS	BATCH SIZE	NO. OF STRINGS	ACCURACY
3	10	1000	0.5521
5	10	1000	0.5681
3	15	2000	0.5779
5	15	2000	0.5916

Table 1. Performance Matrix

Table 1 shows the combination of different parameters which were used to get the best possible accuracy. Similar to the hyperparameters in classical machine learning, Quantum machine learning also needs hyperparameter tuning in order to save the model from problems like overfitting and underfitting. Even quantum machine learning models must be generalized. The hyperparameters for quantum machine learning approach discussed in this report are number of samples which refers to number of samples used, number of qubits, number of epochs and number of batch size. One important consideration while using Quantum machine learning is, even after the simulation of quantum circuits it needs a large amount of time to process qubits. And if more qubits are fed to the circuit, since google cloud was used, the kernel might crash. So, images were resized to (4,4) and this is a major drawback since there is loss of information. So, tuning all other hyperparameters such that the available data could give the best possible results was a major task in this approach. We could achieve the best accuracy when number of epochs was set to 5, batch size of samples was 15, and number of strings used for training were 2000. Time taken to train the quantum model was around 45 minutes. The accuracy keeps on changing since every time a new data frame, in this case a new qubit is considered and the average calculator changes on the basis of it.

5. CONCLUSION

The report consists of the results for classification of the satellite images using a Quantum Machine Learning approach. We have used a simulation of Quantum Computing and hence the results may vary drastically if a real quantum computer was used to solve this problem. The word ‘drastically’ refers to the time needed to train the model and also the number of qubits processed. Along with Quantum computing, Quantum Machine learning has a wide scope in future. The recent developments and the ongoing work depict the promising future of this field. We hope to simulate research by further trying and combining different algorithms, either quantum, classical or hybrid for classifying images and use it for various Computer Vision applications.

6. DISCUSSION

The major part of concern was using quantum machine learning is not a method in traditional computer vision. However, we can use it for image classification by converting the images into the data form needed i.e. qubits. Hence, using Quantum Machine Learning for image classification qualifies to be a Computer Vision task. Google has been developing many algorithms to promote the use of tensorflow-quantum.

Presently, it has been developing the Quantum Convolutional Neural Network algorithm and hence, it constitutes as a future scope to the project specified in this report. Tech giants like Google and IBM are leading the Quantum development race. In future, it is possible that quantum computation might replace the classical computing methods. This might be the possible reason that quantum machine learning algorithms by Google and their research is public. They want to promote the use of this technology and make it open source so that it will be easy for us to adapt and know Quantum computing methods.

Furthermore, there is still a lot to improve in terms of providing quantum computers to actually work on. At present, there are many cloud computing options like IBM Watson, Google cloud, etc which provide runtime environments like Graphics Processing Unit, Tensor Processing Unit, etc. for training and testing different models. But there is no such service or platform present for quantum computers. So, this is a scope for development. This is just the beginning of Quantum Machine Learning and with the future development, there will surely be a buzz and advantages of this technology.

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