Addressing Climate Change Through Quantum Computing

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Figure 1: Sustainable development goals

1 Introduction

The United Nations has set out 17 sustainable development goals to ensure a better future for us all. Goal 13 of the United Nations Sustainable Development Goals (SDGs) [2] focuses on taking urgent action to combat climate change and its impacts. Climate change is one of the most pressing challenges of our time, and its impacts are felt globally. Each year we hear about the annual rise of the earth's temperature, along with all the natural disasters that follow as a results of climate change.

In this report, we aim to address this issue of climate change by utilizing quantum computing techniques to predict annual temperature changes. This will give us insights into how quantum computing can play a role in discovering which countries will be affected by climate change in the future, help bring awareness to this issue, and allow them to pre-emptively implement countermeasures.

2 Methodology

2.1 Problem Identification

The specific problem we are addressing is the prediction of annual temperature changes for each country. Accurate temperature predictions are essential for monitoring climate trends and taking action against climate change. We have chosen this problem due to its high relevance to the SDGs and its potential impact on climate adaptation and mitigation efforts. Countries can use this model to predict their annual temperature increase based on historical data. This can help them to implement solutions to decrease the rate of temperature increase and prepare for the consequences such as rising sea levels, exaggerated temperatures, droughts, floods, and much more.

2.2 Dataset Selection

To address the problem of predicting annual temperature changes, we used the data provided by Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) [1], which provided valuable information relating to climate change. We split this into two distinct datasets: one containing the annual change in temperature per country, and the other containing the number of disasters per country per year. Both datasets were acquired in a raw format and required preprocessing.

2.2.1 Data Preprocessing

The raw data obtained from the website had to undergo several preprocessing steps to make it suitable for our project. The preprocessing steps included:
1. **Data Cleaning**: The datasets contained missing or inconsistent entries. We cleaned the data by removing or imputing missing values, ensuring that it was free of errors and anomalies.
2. **Data Integration**: The annual change in temperature dataset and the disaster dataset were combined into one comprehensive dataset. This integration was performed by matching data entries by the name of the country.

2.2.2 Data Selection

Our project focused on predicting annual temperature changes using a quantum neural network. To train the model, we selected data from the years 1991 to 2022. This time frame was chosen to capture relevant historical data while ensuring that the dataset remained manageable for training.

2.2.3 Data Splitting

To evaluate the performance of our quantum neural network model, we divided the cleaned and integrated dataset into two subsets: a training set and a testing set. We allocated 75% of the data for training and the remaining 25% for testing. This data-splitting approach ensures that we have a distinct dataset for training the model and another dataset for assessing its predictive capabilities. To create labels for training and testing, the last entry (2022) for each country was taken as the label for that country, whereas the training and testing data was all the entries between 1991 and 2021. The shapes for the different datasets are shown below:

```
training data       torch.Size([2, 150, 30])
test data           torch.Size([2, 50, 30])
training labels     torch.Size([2, 150])
test labels         torch.Size([2, 50])
```

The training and testing data will be used to feed into our quantum neural network, allowing us to assess its accuracy and performance in predicting annual temperature changes for different countries.

2.3 Algorithm Development

Our approach involves designing and developing a near-term quantum computing algorithm. We will leverage a quantum neural network to predict annual temperature changes. The choice of this quantum algorithm is based on its suitability for tackling climate-related challenges, and to explore how certain quantum principles can be used to improve classical approaches.

3 Results

3.1 Implementation and Execution

To address the problem of predicting annual temperature changes, we have implemented a quantum-enhanced solution using a Variational Quantum Circuit (VQC). The following section outlines the key components of our implementation and execution:

3.1.1 Quantum Device Configuration

We begin by defining a quantum device using PennyLane. The device "default.qubit" is chosen, and it is configured with 10 qubits (wires) to facilitate quantum computations. This device is essential for simulating quantum circuits and evaluating quantum-based predictions.

3.1.2 Cost Function

The cost function is a crucial element in our implementation. It quantifies the error between predicted and actual temperature changes, incorporating both temperature and disaster data. The cost function is defined as follows:

$$\text{Cost} = \sqrt{\alpha \cdot \text{Temperature\_Distance} + \beta \cdot \text{Disaster\_Distance}}$$

Here, α and β are hyper-parameters that can be adjusted to balance the contributions of temperature and disaster data to the overall cost. The cost function uses the Euclidean distance between the predicted output and the true output. Thus when the loss function is minimised, the distance between the predicted output and the true output will be minimised.

3.1.3 Data Encoder

A data encoder is implemented that takes input in the range of $[0, 1]$ and converts the decimals it to the binary representation. In the quantum circuit, a X-gate is applied to each bit that is 1.

3.1.4 Variational Quantum Circuit (VQC)

The heart of our implementation is the Variational Quantum Circuit (VQC). After the data has been encoded, it is passed to the VQC, where that takes two key inputs: x and params.

- x: This input represents the data to be processed by the quantum circuit. It is used to encode relevant features that influence temperature predictions.
- params: These are the trainable parameters of the VQC. The circuit includes n quantum gates, where n is the number of qubits specified (in our case we use 10 qubits). Each gate is defined using the RY gate, with parameters controlled by params[i].

The VQC aims to learn the optimal set of parameters that minimizes the cost function, thereby improving the accuracy of temperature change predictions.

3.1.5 Hybrid Model Integration

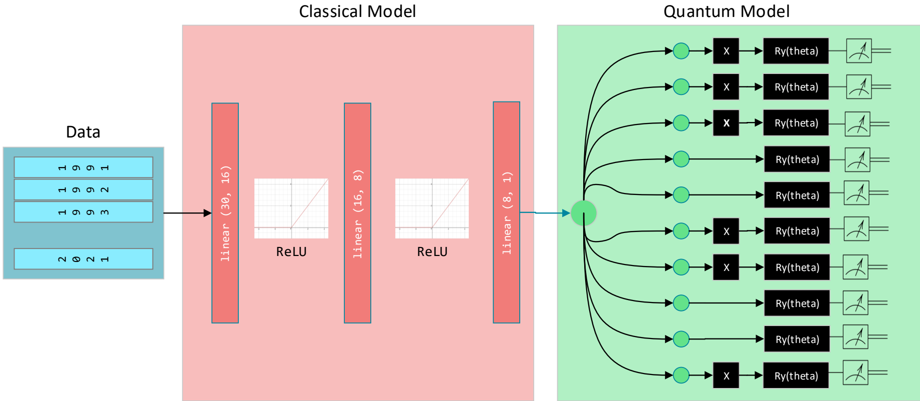

Figure 2: Hybrid model implementation

We integrate the quantum circuit with a classical neural network. The Hybrid Model combines the classical neural network's output with the output of the quantum circuit. This integration allows us to leverage the strengths of both classical and quantum computing for enhanced predictions. The classical model is defined as a three-layer feed-forward neural network, with a ReLU activation function between each linear layer to introduce non-linearity. The quantum model is used to fine-tune the output from the classical model.

3.1.6 Training and Optimization

The implementation proceeds with model training and optimization. The model is trained on both the temperature and the disasters data. The Adam optimizer is employed to optimize both the classical neural network's parameters and the VQC parameters. For the classical model we used a learning rate of 0.001, while for the quantum model, we used a learning rate of 0.01.

3.1.7 Evaluation and Testing

To assess the performance of our quantum-enhanced model, we evaluate it using a separate testing dataset. The accuracy of our predictions is assessed based on mean squared error (MSE) calculations, which is ideal to accurately test the model's ability to predict annual temperature changes.

MSE		alpha	
		0.5	1.0
beta	0.5	0.046	0.156
	1.0	0.098	0.093

Table 1: MSE results for different alpha and beta values.

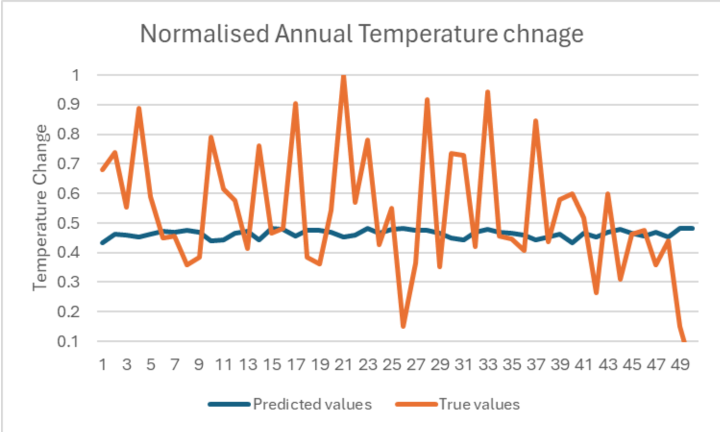

Figure 3: True vs Predicted annual temperature change for each country

4 Discussion

4.1 Interpretation of Results

In this section, we will interpret the results obtained from our quantum algorithm. The accuracy and performance of our model are evaluated through the calculated mean squared error (MSE). A lower MSE indicates better performance in predicting temperature changes.

Figure 3 shows how the model predicts the temperature for each country compared to the true temperature. One can see clearly that the predicted values is smoother end less erratic, but that it follows the patterns of the true temperatures. From Table 1, one can see that the Mean Square Error is the lowest when the alpha and beta are similar. This indicates that the model benefits from having both datasets implemented and equally weighted.

This shows that the Hybrid model is successful in predicting the annual change in temperature for a country given the historical data. The results also indicate that the model benefits from having both the temperature and the disaster data to learn from.

4.2 Challenges and Limitations

Every project faces challenges and limitations. We will discuss any challenges encountered during the implementation of our quantum algorithm and acknowledge its limitations. Some of the challenges we faced (and overcame) included how to handle the missing information in the dataset, how to convert the data into a form suitable for the quantum circuit, and finding the optimal choice of model architecture. Furthermore, one of the biggest limitations for quantum neural networks is the accuracy of the results when using more qubits. Companies all over the world is working towards building quantum machines with more qubits to address this problem.

4.3 Future Directions

As quantum computing continues to advance, there are opportunities for further research and development in addressing climate change. With this advancement, one would be able to implement a similar system with more qubits, or use an improved quantum circuit, in order to increase the accuracy of the model. One could also add more data to the model, as the years progress and more information is gathered.

5 Conclusion

The implementation of a hybrid neural network, comprising both classical and quantum neural networks, for predicting annual changes in surface temperatures in countries marks a significant stride in contributing to climate monitoring and sustainable development efforts. This innovative approach harnesses the computational power of quantum computing to enhance the accuracy of temperature predictions based on historical climate data and various relevant factors. As we witness the increasingly visible impacts of climate change, this technology underscores the importance of anticipatory and adaptive actions. Nevertheless, continuous refinement and enhancement of these models are essential as we gather more data and deepen our understanding of quantum computing. Ultimately, the hybrid neural network method contributes to the broader effort to combat global warming by leveraging classical and quantum computing to support sustainable decision-making and foster a more environmentally responsible future.

References

[1] FAOSTAT. *Annual Surface Temperature Change*. 2022. URL: `https://climatedata.imf.org/pages/climatechange-data`.

[2] UNESCO. *UNESCO and Sustainable Development Goals*. 2021. URL: `https://en.unesco.org/sustainabledevelopmentgoals`.