WEATHER FORECASTING USING QUANTUM-BASED LSTM: A COMPARATIVE ANALYSIS

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OBJECTIVES

QLSTMS for weather forecast are more accessible and allows it to have the ability to take advantage of a lesser memory utilization, better parallelization and let us do the following:

1. Preprocess hourly weather data with 87672 data points.
2. Create a QLSTM consisting of blocks of VQCs.
3. Show a faster convergence to a minima.
4. Lesser tunable parameters due to parallelism

MATERIALS & METHODS

The following technologies were required to complete the research:

- Tensorflow's Qiskit
- Pennylane AI
- Jupyter for additional computation
- Saskatoon – weatherstats historical 30 year data

The following equations were used for statistical analysis:

$$H|0\rangle = \frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle \quad (1)$$

$$Ry(\theta)|\psi\rangle = \cos\frac{\theta}{2}|0\rangle + \sin\frac{\theta}{2}|1\rangle = \left(\cos\tfrac{\theta}{2}\ \sin\tfrac{\theta}{2}\right) \quad (2)$$

The above equations describe some of the quantum operations that are applied onto multi qubit systems of which are VQCs are made of. These operations rotate and manipulate the states of qubits before calculating an expectation measurement value for classical processing.

REFERENCES

[1] ANTONIO ROBLES-KELLY TARIQ M. KHAN. Machine learning: Quantum vs classical. 2020.

[2] Yao-Lung L. Fang Samuel Yen-Chi Chen, Shinjae Yoo. Quantum long short-term memory. 2022.

INTRODUCTION

QLSTMs leverage quantum mechanics to improve the performance of LSTMs by using qubits instead of classical bits. This allows for potentially quicker selective computations and the ability to handle high-dimensional data using quantum algorithms such as PCA. QLSTMs can be useful for tasks such as image/speech recognition and encryption due to their ability to search through large datasets in parallel. Traditional LSTMs are limited by the curse of dimensionality, but QLSTMs can potentially handle high-dimensional data more effectively.

RESULTS 2

The following table presents the comparison of n-Qubit QLSTM on weather forecast data with a traditional Stacked-LSTM.

Model	Train Loss	Test Loss
LSTM	0.00013	0.00019
4-Qubit QLSTM	0.0.000194	0.000195
6-Qubit QLSTM	0.000144	0.000176
8-Qubit QLSTM	**0.00075**	**0.00010**

Table 1: Comparision of formulated LSTM Models

The following table highlights where QLSTM stands at predicting temperatures as opposed to traditional BiLSTM and SFA-LSTM.

Model	Test Loss
BiLSTM	0.136
SFA LSTM	0.871
QLSTM	**0.00010**

Table 2: A Comparative Analysis of QLSTM , vanilla BiLSTM and SFA-LSTM

PLOTTED RESULTS

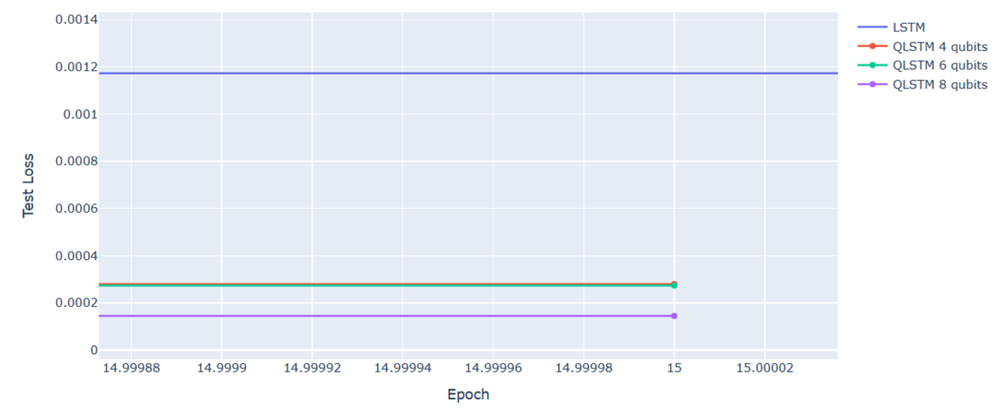

Figure 1: All QLSTMs VS LSTM Test Loss

For QLSTMs, we trained 4, 6, and 8-qubit neural networks using PennyLane with Adagrad optimizer and 15 epochs. The 4-qubit model had test loss decreased from 1.0436 to 0.00028, and execution time per epoch between 2970 and 4646 seconds. The 6-qubit model achieved a test loss of 0.0002375 , while the 8-qubit model achieved a final test loss of 0.000178 after the first epoch's extreme test loss of 1.03. Despite the long execution time per epoch, the models showed potential in making accurate predictions on the input weather series.

The 8-qubit quantum network uses one QLSTM layer with 3 V-rotations per qubit, achieving good performance on a specific task after 15 epochs of training. Test loss improved from 1.03 to 0.000178, indicating good generalization to unseen data. However, the execution time of each epoch was relatively high, and memory space requirements could increase exponentially. Nevertheless, this is a significant step forward in the development of quantum neural networks, which have the potential to revolutionize data-sequencing and time-series forecasting. Expect future hardware and software improvements to reduce execution time.

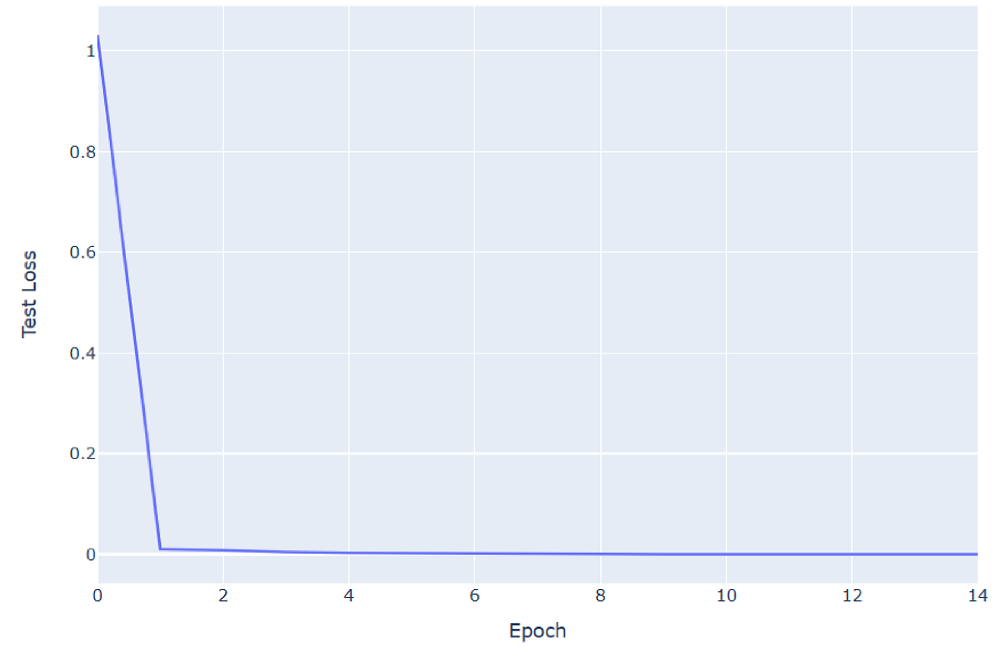

Figure 2: 8-Qubit System Test Loss vs Epochs

CONCLUSION

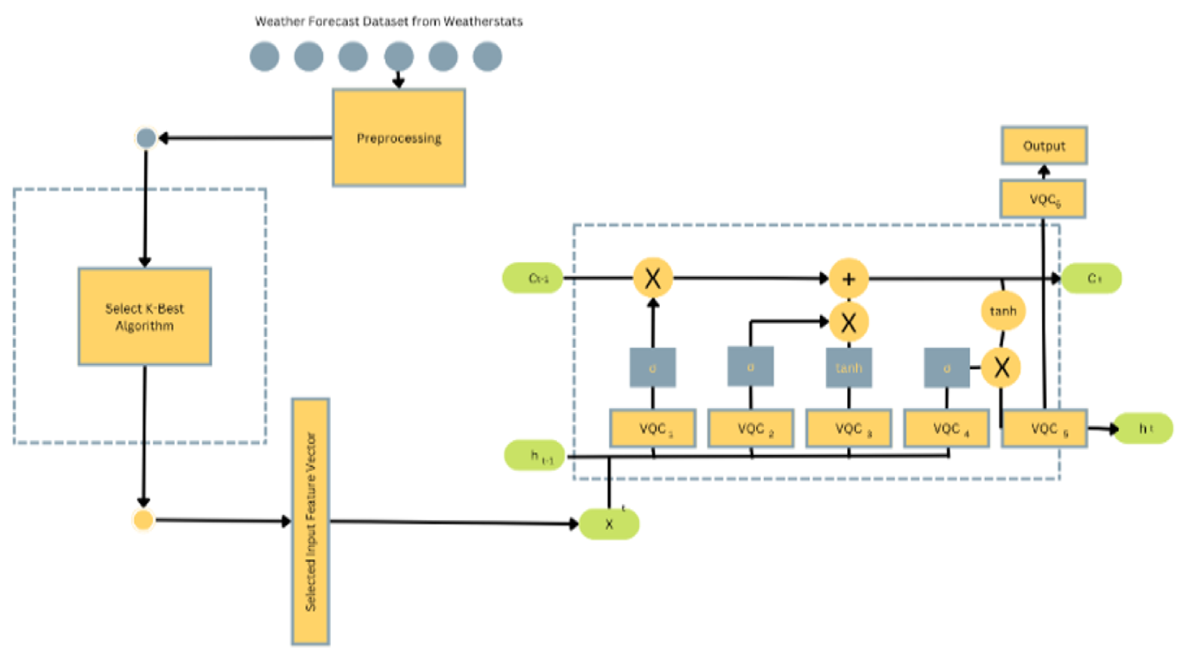

Figure 3: Architecture of QLSTM

- The QLSTM network displays faster convergence and better trainability compared to classical LSTM models for time-series prediction.
- However, the need for a real quantum system with more powerful processing power is essential for improving this technique.
- QLSTMs have vast potential, but are sensitive to noise and other errors. Further research and development of quantum neural networks could revolutionize artificial intelligence.

FUTURE RESEARCH

Quantum-LSTMs have limitations such as long training times, hybrid approach issues, and hardware unavailability. They're also sensitive to noise and errors that cause state collapse, leading to information loss. Quantum neural networks may transform computing and data processing but require continued research to overcome these challenges.

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