Quantum Computing is a new paradigm that promises a transformation in the way we approach problems in quant finance. It promises improvements to current approaches, brings speed-ups, and improves accuracies in AI/ML, optimization, and simulation problems. One of the fundamental building blocks in finance is to predict the price of an asset that has a dependency on several macro and micro factors, behaviors, and dynamics of the market. Several approaches have been proposed for price prediction problems using classical methods and it is expected that we can further enhance the predictions using quantum approaches. The objective of this paper is to effectively predict the price of the FTSE 100 index based on historical data using the quantum approach and benchmark this against the classical approach.

In this report, we have presented two quantum approaches for stock price prediction. First is quantum LSTM. This involves extending the classical LSTM into the quantum realm by replacing the classical neural networks in the LSTM cells with a ’hybrid’ circuit. The hybris circuit is the stack of dense and quantum circuit layers. Second, we propose a novel quantum neural network approach.

The novel quantum neural network approach involves first Passing the ‘n’ days feature data through the Quantum circuit. This generates the latent factors for each day. Second, apply a flattened layer to the latent factors of the past ‘n’ days and place them in a sequence. And at last, Bringing the nonlinear interaction between these latent factors for the last ‘n’ days through a stack of dense and quantum layer to predict the future.

To model quantum circuits in both quantum LSTM and quantum proposed ANN we have used multi qubit data reuploading and have shown its significance. To realize multi-qubit DRC We divide out input data features X in a set of three (X1, X2, etc). Then we encode the set of three data dimensions into multiple qubits using Single qubit arbitrary rotation. Then we add a layer of learnable parameters using single qubit arbitrary rotation. Then add an entanglement layer. By repeating this stack of data uploading layer, learning parameter layer, and entanglement a a highly complex feature can be created in an attempt to improve the learning capacity of the algorithm.  The Measurement from all qubits is the expectation value of Pauli Z.

The effect of data reuploading is analyzed for both 4-qubit and 6-qubit quantum circuits when using Quantum LSTM. The data reuploading concept helps in better learning as training loss decreases more for DRC than NO-DRC after a certain epoch.

As a result, when experimenting with Quantum LSTM we observe that the 6 qubits QLSTM can provide a comparable solution with classical LSTM and requires less computational parameters (1143 against 5387). Also, the loss with quantum LSTM was less for the same number of parameters. As a result, when experimenting with Quantum ANN we observe that Quantum ANN gives comparable results to its classical counterpart and requires fewer computational parameters (1355 against 3766). Also, Quantum ANN Learns more information in the initial few epochs compared to the classical approach. Thus, The performance of the quantum approach with fewer learning parameters (Low qubit count and Low overall depth of circuits) shows its advantage in recognizing patterns in data or making predictions. The Quantum approach learns more information in the initial few epochs compared to the classical approach. Quantum performance could improve with increasing quantum circuit depth and number of qubits.

Reference:

Chen, Samuel Yen-Chi, Shinjae Yoo, and Yao-Lung L. Fang. "Quantum long short-term memory." In ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 8622-8626. IEEE, 2022.

Reference to Final Defence Presentation : <https://github.com/rbanerjee7/04360111/blob/524a26dc06b8980b3336d98d81d71955e1748615/Phase-2/TCS%20QC%20-%20Final%20Defence%20Presentation%2004360111.pptx>

Reference to Code base: <https://github.com/rbanerjee7/04360111/blob/main/Phase-2/Test_script.txt>

Reference to Final Test Results: <https://github.com/rbanerjee7/04360111/tree/main/Phase-2/Final_Prediction>

Reference to the Solution Approach document: <https://github.com/rbanerjee7/04360111/blob/main/Phase-2/Challenge_4_report_04360111.pdf>