Quantum Machine Learning Applications for 6G: A Channel Estimation Scenario

Nhien Q. T. Thoong[1], Adnan Ahmad Cheema[2], Octavia A. Dobre[1], and Trung Q. Duong[1, 3, *]

[1] Faculty of Engineering and Applied Science, Memorial University, St. John's, NL A1C 5S7, Canada.

[2] Advanced Wireless Technologies Lab, School of Engineering, Ulster University, Belfast, BT15 1AP, UK.

[3] Centre for Wireless Innovation, Queens University Belfast, Belfast, BT7 1NN, UK.

* Corresponding author: Trung Q. Duong (e-mail: tduong@mun.ca).

Abstract:

The sixth-generation (6G) wireless communication networks are attracting global attention from researchers and industries with an aim to overcoming the challenges faced by the previous communication networks (e.g. 5G and xG). Due to considerable benefits achieved by non-orthogonal multiple access (NOMA) in wireless systems, it is widely investigated in various recent research studies. Reconfigurable intelligent surface (RIS) and NOMA can support each other to increase the performance of the 6G system. Channel estimation plays a crucial role in an integrated RIS-NOMA system by providing the necessary information to optimize system parameters, manage interference, and adapt to the dynamic nature of the channel. Quantum machine learning (QML) framework has gained growing attention in many fields, where classical data embedded in quantum bits (qubits) can benefit from quantum phenomena to reduce the network size and speed up training time. It is a new paradigm, which can provide considerable computational benefits for many domains, especially in addressing problems of 6G wireless communication. This work proposes a QML-based channel estimation method using a convolutional quantum long-short term memory (CNN-QLSTM) model, which takes advantage of CNN and QLSTM, for RIS-NOMA assisted 6G communication system. One of the most significant advantages of CNN mode is their ability to perform automatic feature extraction or feature learning. On the other hand, long-short term memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to overcome the vanishing gradient problem in traditional RNN models. The key feature of LSTM is their ability to capture long-term dependencies in sequential data. Quantum LSTM (QLSTM), where LSTM is implemented with variational quantum circuits (VQCs), is a framework that has been shown to have faster learning ability and stable convergence than classical counterpart. Our results show a comparison of both classical and QML models and performance evaluation based on different performance metrics.

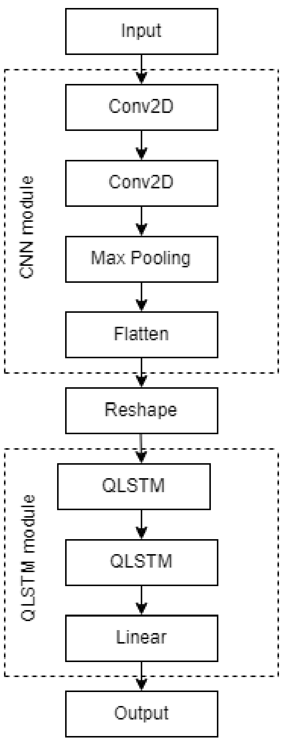

Figure 1. CNN-QLSTM model.

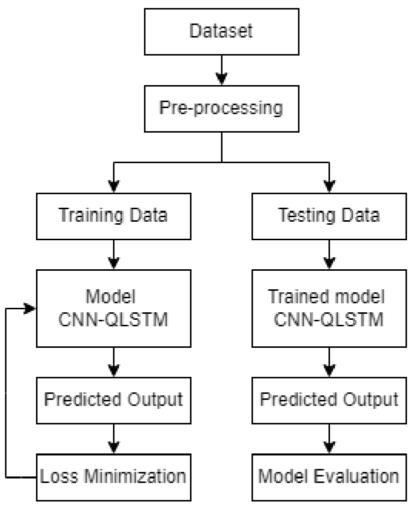

Figure 2. Workflow of model training and testing.