Undergraduate Research and Education in Quantum Machine Learning

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***Abstract*—This Work-In-Progress paper describes a program in quantum machine learning launched in the academic year of 2021-22. The program engaged undergraduate students from STEM areas with faculty and industry mentors. Because of the COVID-19 conditions, this undergraduate engagement was offered in a virtual format. In 2022, some face-to-face meetings with presentations were also held. The program included: a) training in machine learning with quantum simulators, b) weekly presentations, and c) semester end presentations. The assessment of the program included surveys, interviews, and presentation observations. Challenges and opportunities from virtual engagement were also part of the assessment.**

Keywords—quantum computing, machine learning, AI, quantum audio and image processing

I. INTRODUCTION

Quantum computing is a growing field that promises to elevate computing speeds by as much as 100 million times relative to classical computing. Although the technology is still at an early stage, it captured massive research investments from industry and federal labs. In fact, the White House Science and Technology office stated that quantum information systems would likely enable "breakthroughs in numerous fields," including Artificial Intelligence, Big Data, and sensing. Federal initiatives also emphasized the need for workforce development, starting with undergraduate students and even at the K-12 level.

This work in progress paper (WIP) describes an undergraduate research and education experience in quantum machine learning (QML) [1-2]. Undergraduate student participants engaged in QML training and research studies that focused on machine learning (ML) algorithms designed to run on quantum computers. In addition to students, this project also included a community college instructor that participated in the research, undergraduate curriculum development, and outreach activities. The proposed WIP paper describes the methods and assessment used for remote delivery in the summer and fall of 2021 during the COVID-19 period. The program began with pre-training of participants using video streamed modules that provided the basics of ML. In parallel, participants attended sessions where they presented their QML literature review and their research progress. Challenges included training students both in ML and quantum systems in limited time and with minimal access to actual quantum computers.

Program components included: a) training students in QML software implementation, b) reviewing live online participant work, c) preparing the participants in establishing scientific documentation, and d) guiding the students in developing results for possible publication. Students worked on QML for imaging and audio classification. All students used QML for detecting and classifying images of graphical characters. One of the students worked on designing QML implementations for classifying audio signatures. By embedding students in QML training and research, they acquired skills in terms of knowledge on data preprocessing, feature extraction, ML, and implementation in Python. Participants learned how to profile algorithms in terms of performance and complexity and how to then present results in terms of confusion matrices. Interactive video conferencing sessions guided participants in the preparation of their presentations for delivery to academic and industry audiences. One of the challenges was getting access to quantum computers which are currently very limited and expensive. Researchers were able, however, to access quantum simulators and worked with IBM Qiskit tools. Students were trained to use the simulator to develop quantum gates and realize quantum neural networks (QNNs) and quantum Fourier transforms. An example of the process used to design a quantum circuit for a QNN is shown in Fig. 1.

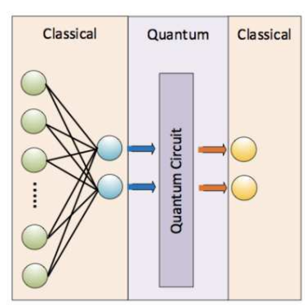

Fig. 1. *A hybrid realization of a QNN [1].*

The weekly program consisted of a) orientation and knowledge checks, b) evaluations of progress, and c) scientific documentation of research in STEM journal format. Participants presented their results weekly to faculty and received feedback. To assess the impact of the training and research experience, an external evaluation plan was developed that included both formative and summative assessments. An assessment specialist interviewed participants to evaluate training and research progress. This paper will discuss the research background in QML, the various student research projects, evaluation results, and future plans for the program.

II. Research Focus and QML Training

Research and education in quantum information processing (QIP) focus on computational aspects of quantum systems based on the laws of quantum mechanics. Prior work on QIP includes QML [1]-[4], QNNs[5]-[8], Quantum Cryptography [9]-[11], Big Data [12]-[13], and Quantum Audio processing [14]-[15]. In addition, several efforts in quantum education research have been launched across various fields [16]-[18].

The undergraduate training program recruited students from STEM fields, including Physics, Electrical Engineering, Biological Systems, and Computer Systems. The intellectual focus of the program is on establishing foundations to create a workforce in QML, starting with undergraduate students. The proposed paper describes the methods, processes and assessments that were used in 2021-22 to train undergraduate (UG) students in machine learning and quantum ML simulations for various applications. The program began with recruitment and pre-training using video-streamed modules that provided the basics of ML [19]-[20]. In parallel, the UG participants began their research by compiling background content in their respective projects and applications. Students developed first their skills in QML simulations, where they were guided by industry and faculty mentors to simulate classification using the MNIST data set [19]. The students also began documenting their literature reviews in their respective QML application areas. Challenges included: a) designing software implementation content via video conferencing sessions, b) reviewing live online participant work and providing feedback, c) guiding the participants in establishing documentation and presentations, and d) guiding the participants in developing research results for possible publication. In terms of skill building, all participants worked on ML basics and Python programming. Algorithm performance assessments typically involved producing confusion matrices, convergence curves for NN training, and tabulating accuracy of classification in the training and testing phases. In addition, participants explored ways to assess complexity in in terms of programming lines of code, CPU time and memory requirements of the algorithms. The profiling of QML algorithms presented additional challenges as simulating quantum computing on different simulators involved different quantum circuit models. Meetings included delivery of synchronous content via video conferencing sessions and asynchronous content delivered through pre-recorded modules and Google notebooks. Daily pre-recorded seminars were also delivered to provide background and exposition in multi-disciplinary applications of sensors and machine learning. Participants presented their software simulations and results weekly and received technical feedback. To assess the program impact, an evaluation plan was developed that included both formative and summative assessments. At the end of the program, participants gave a final research presentation and provided a research report. The final presentations were given to a diverse audience in the local IEEE Education Chapter, which included faculty, graduate students, an evaluator, and industry representatives.

III. Research Projects

Participants started their initial training by following a series of ML modules for classical computing. To perform the hands-on ML programming, a series of Python programming tutorials using Google Colab were used. Colab notebooks are user-friendly and enabled the participants to learn fundamental ML concepts with minimal syntax issues. Google Colab hosts online Jupyter Notebooks, which include both documentation and code. Training started with descriptions of K-means clustering and then continued with descriptions of Support Vector Machines (SVM), Neural Networks (NN). and a brief exposition to Positive-unlabeled (PU) learning. Simulations with an object-oriented program [20] were also used for the initial introduction to machine learning.

Undergraduate participants worked on quantum machine learning solutions for audio classification and cryptography. Additional work was also performed in Quantum Fourier transforms for compression and Galaxy morphology classification. Brief descriptions of four research projects are presented below.

A. Project 1: QML for Galaxy Morphology Classification

The large volume of data on astronomy requiring analysis in the field of astronomy has been a great challenge for this community [21,22]. The use of quantum computing could allow astronomy to reach unprecedented breakthroughs. This project explored the use of hybrid quantum-classical convolutional NN to classify galaxies by morphology. Figure 2 illustrates Hubble's galaxy classification scheme.

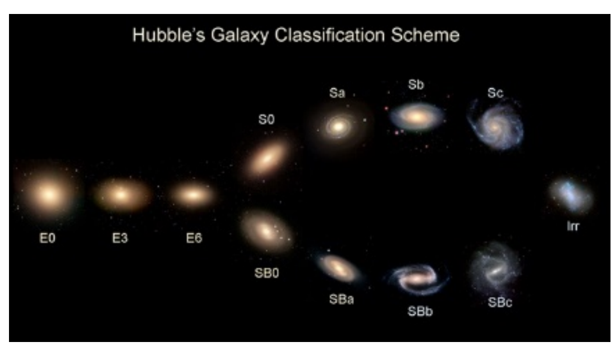

Fig. 2. *Image of Hubble Galaxy Classification (from Astro.physics.uiowa.edu) [22].*

B. *Project 2: Audio Classification using Q-CNN*

In this research project, the student studied the use of quantum neural networks in audio signature detection and classification. More specifically, a deep learning model for detecting breathing pathologies and coughing signatures for various conditions, including COVID-19, were examined. Benefits of using quantum computing include secure and fast computation as well as the ability to deal with vast databases. The project examined the design of a hybrid Quantum-Convolutional (Quanvolutional) Neural Network (Q-CNN) simulation architecture and provided preliminary results in terms classification accuracy. Spectrogram features were extracted from public databases [23]-[24] and classification with the Q-CNN was reported in terms of a confusion matrix. Fig. 3 shows a sample spectrogram for COVID-19 cough. With proper segmentation and feature extraction it can be shown that accuracy in COVID cough detection can exceed 75% [25-26]. A quantum circuit for audio Cough detection was designed and is shown in Fig. 4.

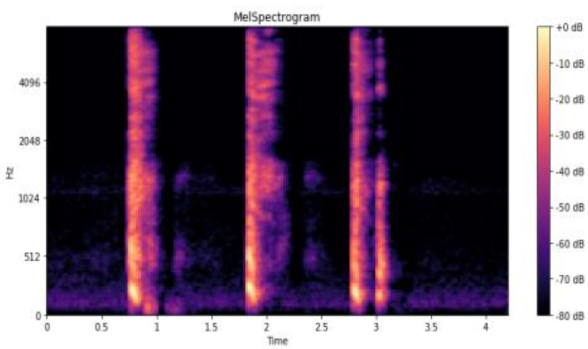

Fig. 3. *LogMel spectrogram generated from COVID-19 cough audio data (data obtained from [23]).*

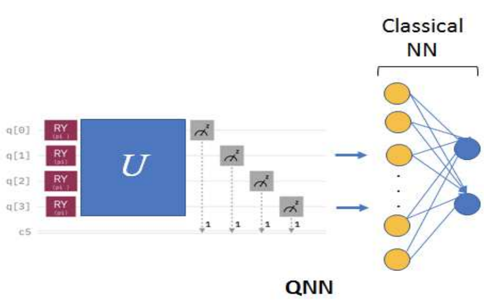

Fig. 4. A hybrid QNN model for audio classification from spectrogram features.

The quantum circuit of Fig. 4 shows the quantum gates and the qubit measurement process. The student working on this project examined and documented the effect of the number of qubits as well as the effect of quantum noise.

C. *Project 3: Quantum Fourier Transforms and Signal Compression*

The training and research on quantum Fourier transfirms focused on signal analysis and reconstruction [30,31]. Quantum circuits were deisgned for a quantum fourier transform (QFT) and an inverse QFT (IQFT) and their effectiveness was tested in terms of resolving frequency components of real and synthetic signals. In addition simulations were run for signal analysis and reconstruction for use in compression applications. Through the process the student learned how to design and assess quantum circuits and simulations. Results were obtained and the student working on this project examined and documented the effect of the number of qubits as well as the effect of quantum noise. The quantum circuits for the QFT and IQFT for 3 qubit implementations are shown in Figure 5. Signal reconstruction was implemented with a speech signal and 70% compression was implemented by retaining a subset of QFT components for reconstruction.

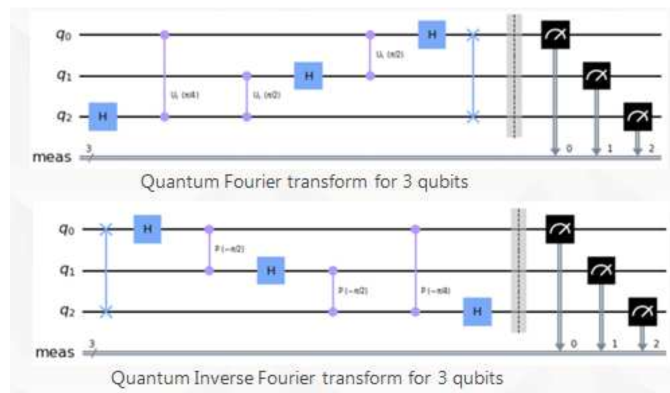

Fig. 5. Quantum circuit for the QFT and IQFT.

D. *Project 4: QML for Cryptography*

This research study focused on encryption technologies where quantum computing may affect protocols and deciphering codes. The problem examined is the protection of NN parameters that may represent proprietary data. Homomorphic encryption [27]-[29] enables operations to be performed on encrypted data without having to decrypt the data in the process. An encryption scheme for a quantum perceptron is introduced as the building block for a more complex QNN. Algorithms are profiled in terms of performance and complexity and results and comparisons of quantum versus classical computing are given. The effect of quantum noise and qubit resolution is also studied. Fig. 6 shows a process of homomorphic encryption. The encrypted data can go through a transform (performing a function, for example), and decrypted with the transform applied to the original data.

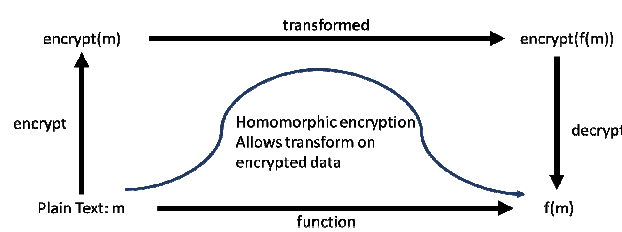

Fig. 6. Process of Homomorphic Encryption.

IV. Student Research and Education

The students involved in this program worked together with their mentors on their research and shared their experiences, algorithm and software challenges, and scientific documentation components. A common thread in all projects was training in machine learning, Python programming, and quantum computing simulation programming. These shared experiences and interactions was important as it helped students overcome problems during their study and also become aware of each other's research and disciplines. Students compiled results in final reports, which served as a starting point for a future, co-authored conference submission with their mentor. For this reason, students were guided to develop their reports in IEEE format. In addition, from the beginning of the research experience student participants developed working documents and received frequent feedback for improvement. Some of the students were able to co-author conference papers on their quantum research [32-33].

V. Assessment

Evaluation and assessment of this undergraduate research experience focused on the following key questions: 1) *Does the program provide knowledge?*, 2) *What were participants' experiences in the program?* and 3) *What skills did participants gain?*

A mixed methods approach was utilized to assess the program using both formative and summative assessment protocol. Retrospective pre-test items were used to assess the extent to which the participants gained knowledge from the program. Specifically, they were asked to rate their preparedness "prior" to their participation and "presently" at the end of the program.

Participants reported that being in the program gave them experiences they otherwise would not have gained such as collaborating with a diverse group of researchers, learning more about different types of research, and learning about machine learning. Participants reported high levels of satisfaction with the training topics, specifically Introduction to Python, MATLAB, PCA Theory, and K-Means Code. All students successfully completed the analysis of data on their research projects and presented their findings to the faculty team, industry, colleagues, and peers.

Participants in the program took pre- and post tests. Here we report on results relating to student problem solving skills. As shown below in Figure 7, students reported gaining problem solving skills in the following areas: interpreting data analyses, statistically analyzing data, designing an experimental test of a solution to a problem, formulating a research hypothesis, locating primary research literature, and understanding primary research literature.

VI. Work In Progress

The QML project continues in 2022 and activities will expand to include several additional machine learning applications. New students will be recruited and will engage in the program in 2022-23. Training adjustments will be made for improvement based on evaluation feedback. For example, quantum ML training modules will be created so students can prepare better prior to the start of their research and training project. Students will also be provided additional training on presenting research to stakeholders.

New program components will deal with assessing noise and complexity in QML. The team of faculty and graduate students that serve as mentors to undergraduate research and training have been developing research and training content to assess quantum algorithm complexity for different simulators. In addition, the team of mentors is developing content on quantum noise models and quantum error correction algorithms. Although, these are advanced concepts qualitative and software models will be developed to transition this knowledge to undergraduate researchers next year.

VII. Conclusion

This work in progress paper presented an undergraduate research training program in quantum machine learning. The program launched in 2021-22 and engaged three STEM undergraduate students mentored by faculty and industry partners. Most of the content was offered in a virtual format, though towards the spring of 2022 meetings were in person, when possible. The students obtained experiences in using Quantum simulators to design QNN circuits for different applications. Participants learned how to assess results using confusion matrices and also evaluate algorithms in terms of performance and complexity. Evaluation revealed satisfaction with the program. Two of the students graduating this spring of 2022 plan to submit research papers on their studies to IEEE international conferences. One of the students will attend graduate school in Electrical Engineering and one applied for medical school. The program was successful in that students were trained in an area of high priority, they created publishable results and they are very likely to follow careers in STEM research. Assessments provided positive feedback. Undergraduate students that participated this year reported gains in problem solving and specifically in data analyses, experimental simulations and research documentation. The program will continue next year with a new cohort of students.

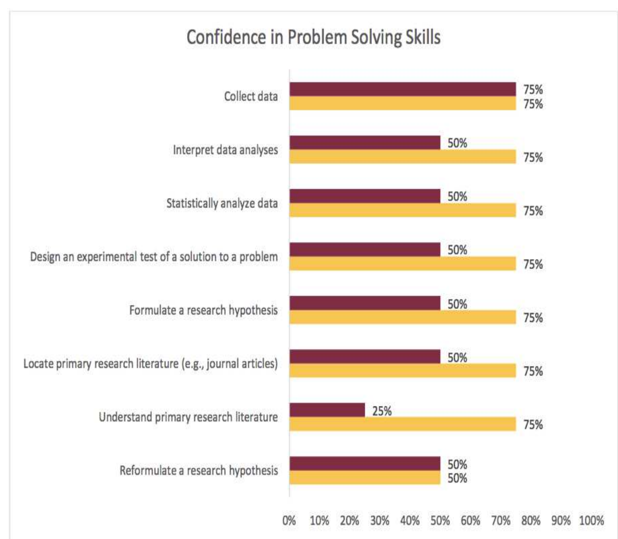

Fig. 7. Pre- and post tests results relating to student problem solving skills

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