Implementation of Quantum Machine Learning on Educational Data

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Abstract: This study is the first to implement quantum machine learning (QML) on educational data to predict alumni results. This study aims to show that we can design and implement QML algorithms for this application case and compare their accuracy with those of classical ML algorithms. We consider three target variables in a high-dimensional dataset with approximately 100 features and 25,000 instances or samples: whether an alumnus will secure a CEO position, alumni salary, and alumni satisfaction. These variables were selected because they provide insights into the effect of education on alumni careers. Due to the computational limitations of running QML on high-dimensional data, we propose to use principal component analysis for dimensionality reduction, a barycentric correction procedure for instance reduction, and two quantum-kernel ML algorithms for classification, namely quantum support vector classifier (QSVC) and Pegasos QSVC. We observe that currently one can implement quantum-kernel ML algorithms and achieve results comparable to those of classical ML algorithms. For example, the accuracy of the classical and quantum algorithms is 85% in predicting whether an alumnus will secure a CEO position. Although QML currently offers no time or accuracy advantages, these findings are promising as quantum hardware evolves.

1 INTRODUCTION

Machine learning (ML) is promising for revolutionizing many domains, including healthcare and education. However, the increasing complexity of contemporary challenges has highlighted the limitations of classical ML algorithms. Handling big data, long model-training durations, and hardware constraints are among the challenges associated with analyzing current data (Nath et al., 2021). Quantum computing seems to be a promising solution in this regard (Alam and Ghosh, 2022), with new possibilities to address some of these challenges.

Quantum machine learning (QML) is a new domain involving the use of quantum computers for information processing (Payares and Martínez, 2023). QML combines quantum computing with ML techniques (Zeguendry et al., 2023), promising improvements in speedups and conventional ML tasks (Alam and Ghosh, 2022). Through further research, quantum algorithms will have the potential to enhance artificial intelligence algorithms, leading to more accurate predictions, faster optimization, and improved ML capabilities (Singh, 2023)

Recent advancements in quantum hardware have advanced the development and application of QML. Improvements in qubit stability and coherence (Vepsäläinen et al., 2022; Bal et al., 2024) as well as an increase in the number of available qubits in quantum processors (IBM, 2023) are expected to enable the execution of more complex and precise algorithms compared to current ones (Boger, 2024). The technology used for generating qubits, an essential component of quantum computers, is rapidly advancing (Ullah and Garcia-Zapirain, 2024). In 2023, IBM surpassed the 1,000-qubit milestone with Condor, which is a 1,121-qubit superconducting quantum processor built using the cross-resonance gate technology (IBM, 2023).

Herein, we aimed to develop a calibrated, quantum educational-modeling framework to accurately predict the career outcomes of university alumni. To the best of our knowledge, there are no studies on the performance of QML algorithms on educational data. We used a large dataset of a private university

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to predict three target variables: CEO (i.e., whether an alumnus will secure a CEO position), salary (i.e., whether alumni salary will exceed the median salary), and alumni satisfaction (i.e., whether alumni would prefer to study again at the university). As is known, QML algorithms cannot be implemented on classical hardware using Qiskit for high-dimensional datasets (at least without advanced data encoding into quantum states). Hence, this paper proposes a method to reduce dimensions and instances prior to the implementation of QML algorithms. We aimed to examine whether QML algorithms can achieve results comparable to or better than those of classical ML algorithms. Furthermore, we demonstrate that currently, QML algorithms can be implemented in a space with reduced dimensions without affecting prediction accuracy in comparison with implementing classical ML algorithms on original datasets.

Education is a key element of economic development (Hanushek and Woessmann, 2010), and authors of (Ceci and Williams, 1997) stated that a professional gains notable benefits for each additional month or year of schooling. Analysis of alumni results is important for students and the reputation of educational institutions. Future advancements in this analysis are expected to benefit students and educational institutions. This study contributes to educational data mining by exploring and benchmarking QML algorithms on an educational dataset of a private university and highlighting the potential and current limitations of QML algorithms.

The remainder of this paper is organized as follows: a literature review is presented in Section 2. The research methodology is introduced in Section 3. Next, we present the findings of our study in Section 4. Finally, Section 5 concludes this study and outlines future research directions.

2 LITERATURE REVIEW

This section presents the findings of a review of Scopus articles performed to understand the state of the art of publications pertaining to QML applications. The query keywords used were "quantum," "machine learning," and "applications" for article titles. This query was raised on June 26, 2024 and it returned 76 articles. The United States and China have published the most number of articles on QML, highlighting its applications in computer science, physics, engineering, and mathematics.

QML showed a noticeable growing number of publications recently, with a spike observed in 2023. A total of 2 articles were published in 2018, 14 in 2020, and 27 in 2023. Because we aimed to elucidate the state of the art of QML applications, we applied exclusion criteria and a filtration process for articles focused on QML applications using real data. This process decreased the number of analyzed articles to 17.

QML has been applied in diverse fields. In environmental chemical studies, ML-based quantum chemical methods are used to understand the behavior and toxicology of chemical pollutants (Xia et al., 2022). Interestingly, authors of (Lachure et al., 2023) showed that the current progress in QML and quantum computers may lead to technological advancements in climate change research. In biochemical thermodynamics, QML is used for metabolism modeling and prediction (Jinich et al., 2019).

In the healthcare domain, QML is used for drug discovery (Batra et al., 2021; Vijay et al., 2023), oncological treatments (Rahimi and Asadi, 2023), and disease detection (Pomarico et al., 2021; Esposito et al., 2022; Miller et al., 2023; Upama et al., 2023; Prabhu et al., 2023)]. In physics, it is applied in high-energy physics (Wu et al., 2021b; Wu et al., 2021a; Chan et al., 2021; Wu et al., 2022; Delgado and Hamilton, 2022), spintronics (Ghosh and Ghosh, 2023), and particle physics (Fadol et al., 2022).

Several algorithms are pivotal in the current application of QML, including quantum support vector classifier (QSVC), Pegasos QSVC, variational quantum classifier, and quantum neural networks. These algorithms are implemented using various quantum simulators and hardware platforms, such as the IBM Quantum Platform (using IBM Qiskit), Google Quantum AI (using Google Cirq), and quantum computers and simulators (using Amazon Braket quantum computing).

Currently, several studies have achieved comparable results for classical and QML algorithms (Esposito et al., 2022; Wu et al., 2021b; Wu et al., 2021a; Chan et al., 2021; Wu et al., 2022; Ghosh and Ghosh, 2023; Fadol et al., 2022; Gujju et al., 2024). Authors of (Prabhu et al., 2023; Ghosh and Ghosh, 2023) highlighted that QSVC and Pegasos QSVC considerably outperformed a classical support vector classifier (SVC) when using the Aer simulator provided by Qiskit.

Interestingly, classical and QML algorithms currently face difficulty in handling big datasets (Wu et al., 2022; Turtletaub et al., 2020), although future QML algorithms are expected to offer more efficient solutions to handle large datasets (Singh, 2023). However, this will require a higher number of qubits and stability (Nath et al., 2021; Ullah and Garcia-Zapirain, 2024; Wu et al., 2022; Peral-García et al., 2024) along with the addressal of challenges associated with noise reduction and error mitigation in quantum computing (Ullah and Garcia-Zapirain, 2024; Wu et al., 2022; Gujju et al., 2024; Peral-García et al., 2024). Our research seeks solutions to these challenges of QML algorithms.

The current results of the research and application of QML algorithms are only hinting at the beginning of QML applications. As quantum computers become more powerful and accessible, the accuracy and the model-training durations difference between classical and QML algorithms will increase, eliciting new possibilities for QML applications across various industries and sciences.

3 RESEARCH METHODOLOGY

This section presents data, the modeling framework, and validation processes used in this study. Next, we propose the use of principal component analysis (PCA), barycentric correction procedure (BCP), and QML algorithms in the proposal. The proposal intends to enable the practical application of QML algorithms and generate a reduced-dimensionality dataset that preserves data variability while accurately predicting target variables.

3.1 Proposal

Herein, we used a large dataset with approximately 100 features and 25,000 instances. Execution of QML algorithms in simulators is not feasible for large datasets because of memory constraints. For example, one cannot run QSVC on a dataset with 750 instances and 7 features using Google Colab.

Therefore, we propose a methodology to enable the execution of QML algorithms on a reduced-dimensionality educational dataset:

1. **Dimensionality Reduction Using PCA.** We use PCA to reduce the number of features while preserving data variability of at least 90% in the reduced-dimensionality dataset.
2. **Instance Reduction Using BCP.** We employ BCP to reduce the number of instances, which previously did not affect the accuracy even on a small dataset (Ramos-Pulido et al., 2024).
3. **Implementation of Classical and QML Algorithms.** We implement the classic (i.e., SVC), and QML (i.e., QSVC and Pegasos QSVC) algorithms.
4. **Comparison Between the Results Obtained in Step 3.** We compare the results of the classical and QML algorithms.

The Sklearn library was used to fit the SVC model (Pedregosa et al., 2011). The Qiskit library was used to implement the QML models, following the recommendations provided in (Team, 2024; Javadi-Abhari et al., 2024). Qiskit is an open-source quantum computing framework, which enables the development and execution of quantum algorithms on real quantum processors and simulators. We used Sampler from qiskit.primitives to execute quantum circuits and obtain statistical results of measurements.

Further, we processed classical data using QML algorithms by following three steps described in (Learning, 2023): 1) encoding of quantum data or preparation of states, 2) processing of quantum data, and 3) reading and outputting of learning results. Parameterized quantum circuits (PQCs) can be used to implement QML algorithms on near-term quantum devices and are sufficiently versatile to depict a broad spectrum of intricate quantum states (Learning, 2023). In QML, PQCs are typically used for two primary purposes: 1) data encoding, wherein the parameters are determined by data being encoded, and 2) as quantum models, wherein an optimization process determines the parameters (Learning, 2023). We encoded our classical data into quantum states using the ZZFeatureMap method and employed the FidelityQuantumKernel class from Qiskit to generate the kernel. The number of qubits used was dependent on the model and number of features (refer to Table 1 for the number of qubits or components used). In addition, we employed QSVC and Pegasos QSVC from the Qiskit library for classification tasks.

3.2 Barycentric Correction Procedure

BCP followed in Step 2 of the proposal is described in (Poulard and Estève, 1995). BCP relies on the calculation of individual weights and a threshold parameter. The training process involves iteratively adjusting the weights of the barycenters to minimize the number of misclassified values. The algorithm defines a hyperplane $w^T x + \theta$, which separates the input space into two classes. First, we define $I_1 = 1,..,N_1$ and $I_0 = 1,..,N_0$, where N_1 represents number of positive cases and N_0 represents number of negative cases. The barycenters of the classes are defined using the following weighted averages:

$$b_1 = \frac{\sum_{i \in I_1} \alpha_i x_i}{\sum_{i \in I_1} \alpha_i} \quad , \quad b_0 = \frac{\sum_{i \in I_0} \mu_i x_i}{\sum_{i \in I_0} \mu_i}$$

The weight vector w is defined as the vector difference $w = b_1 - b_0$. The range of w is not fixed, as it depends on the relationships between the classes, the distribution of the data, and the scale of the features. This vector is central to the classification process because it defines the orientation of the hyperplane in the feature space. At each iteration, the barycenter shifts towards the misclassified patterns. Increasing the value of a specific barycenter causes the hyperplane to move in that direction.The bias term, θ, is computed as follows:

$$\theta = \frac{\max \gamma_1 + \min \gamma_0}{2}$$

where $\gamma(x) = -w \cdot x$. The range of θ will depend on the positions of the points in the feature space and how the classes are distributed. The bias term θ adjusts the position of the decision boundary. The barycentric correction is calculated by modifying the weighting coefficients. We have

$$\alpha_{new} = \alpha_{old} + \beta \qquad \mu_{new} = \mu_{old} + \lambda$$

where $\beta = \min\{1, \max[30, N_1/N_0]\}$ and $\lambda = \min\{1, \max[30, N_0/N_1]\}$, (Poulard and Labreche, 1995). In some cases, BCP has considerably outperformed the perceptron in time (Poulard and Labreche, 1995).

3.3 Data

The university supplied an anonymized dataset comprising survey responses from alumni regarding their social and economic conditions. In 2023, as a part of its 80th anniversary celebration, the university conducted a survey to assess the social and economic condition of its alumni since its establishment in 1943. The survey invitation was sent to all alumni through email and social media. The Quacquarelli Symonds Intelligence Unit Team and researchers from the university conducted a descriptive analysis of this survey, a report of which can be found in (de Monterrey, 2023).

We did not focus on identifying input features associated with target variables. Instead, we aimed to predict the following output features: "CEO" indicates whether an alumnus has secured a CEO position, "Salary" indicates whether an alumnus' salary is higher than the median salary, and "Satisfaction" indicates whether an alumnus would choose to study again at the university. The input features included age, gender, school attended, campus, level of education, current address, region of birth, parental education and occupation, weekly working hours, years spent working abroad, life satisfaction, and income satisfaction along with evaluations of social intelligence, self-knowledge management, and communication, among others. After transforming the categorical variables into dummy features via one-hot encoding, the total number of features was 104.

3.4 Modeling and Validation

Two experiments were performed to evaluate the differences between the performances of the QML algorithms and the classical SVC. In the first experiment, we employed the proposed method to compare the performances of QSVC and Pegasos QSVC with that of SVC on the same reduced-dimensionality dataset. In the second experiment, we again used the proposed method to compare the performance of the SVC on the complete dataset with those of the QML algorithms on the reduced-dimensionality dataset. Notably, the SVC was trained on the complete dataset, while the QSVC and Pegasos QSVC were fitted on the reduced-dimensionality dataset, i.e., a dataset whose instances and dimensions were reduced using the proposed method.

Effectiveness of the algorithms was assessed via random cross validation (CV), which involved generating five random splits of the complete dataset. For each split, the models were trained on the training set (70%) and their prediction accuracy was assessed on the testing set (30%). The average performance of each model was then determined by averaging the results across the five splits.

The metric "accuracy" was used for each algorithm. The tuned hyperparameters and grid were as follows:

- SVC: C: 1,10,100,1000,10000
- Pegasos QSVC: C: 1,10,100,1000,10000; tau: 100,200,300,400; sample: 1000, 2000, 3000, 4000; components = 8,9,10,11,12
- QSVC: sample: 500, 600, 700, 800; components = 4,5,6

During training, the optimal hyperparameter values were selected via random fivefold CV for each algorithm across each split. The following steps were involved: the training set (70% of the data) was divided into five almost equal splits. For each value in the hyperparameter grid (see the last paragraph, section 3.4), the algorithms were trained on four of the splits and evaluated on the remaining one. This process was repeated five times, leaving out a different split each time so that every split was used for validation once. Average accuracy of each hyperparameter value was then calculated across these five repetitions. The "optimal" hyperparameters were those with highest average accuracy. Finally, the accuracy of the algorithms with the optimal hyperparameters was evaluated on the testing set.

The hyperparameter C was tuned during the training of the SVC on the complete dataset. The sample size and dimensions of the dataset used during the training of the QML algorithms were adjusted to the maximum possible extent with the available computing resources via Google Colab (Research, 2024). An optimal combination of number of samples and number of principal components was identified to allow for effective model training and satisfactory performance. In particular, for Pegasos QSVC, C (the regularization parameter) and tau (number of steps performed during training) were tuned. QSVC could not be trained with > 6 components and > 750 cases; therefore, it was tuned with fewer components and cases. Lastly, for the SVC trained on the reduced-dimensionality dataset, only C was tuned and dimensions same as those of Pegasos QSVC were retained to ensure fair comparison for same sample dimensions.

4 RESULTS

Tables 1 and 2 lists all hyperparameters selected and considerations for each target variable and algorithm. It provides the number of components extracted via PCA, sample size used in each case, and optimal hyperparameter selected during tuning. For datasets created for each target variable, the variability was 92% when the number of components was five and 96% when the number of components was 10, implying that most of the variability was captured. For example, for the target variable "CEO" and the proposed method with Pegasos QSVC, the dataset dimensions were 1,500 with the optimal hyperparameters being $C = 1000$ and $\tau = 100$. Tables 1 and 2 also lists rest of the features.

Table 3 presents the prediction results for the different algorithms and target variables. Overall, the SVC trained using the complete dataset performed the best across all target variables, achieving the highest accuracy for "Salary" and "Alumni Satisfaction." For "CEO," the SVC with the complete dataset and QSVC with $< 4\%$ of the instances retained and five principal components showed comparable results.

The performance of the QML algorithms was observed to improve with increasing number of components and instances. Conversely, decreasing the number of components and instances reduced the performance. This important finding shows that in future, when we can use increasing amount of information, the performance of the QML algorithms may substantially improve.

Table 1: Hyperparameters and Considerations for Classical Methods.

	Target: CEO	
	SVC	BCP + PCA + SVC
Components	All	10
Variability	100%	96%
sample	All	1,500
Hyperparameters	C=1000	C= 10
	Target: Salary	
Components	All	10
Variability	100%	96%
Sample	All	4,000
Hyperparameters	C=100	C= 1000
	Target: Alumni Satisfaction	
Components	All	10
Variability	100%	96%
Sample	All	2,000
Hyperparameters	C=1	C= 1

Abbreviations: BCP: barycentric correction procedure, PCA: principal component analysis, SVC: support vector classifier

Table 2: Hyperparameters and Considerations for Quantum Methods.

	Target: CEO	
	BCP + PCA + QSVC	BCP + PCA + Pegasos
Components	5	10
Variability	92%	96%
sample	1,000	1,500
Hyperparameters		C=1000 tau=100
	Target: Salary	
Components	5	10
Variability	92%	96%
Sample	1,000	4,0000
Hyperparameters		C=1000 tau=100
	Target: Alumni Satisfaction	
Components	5	10
Variability	92%	96%
Sample	1,000	2,000
Hyperparameters		C=100 tau=100

Abbreviations: BCP: barycentric correction procedure, PCA: principal component analysis, QSVC: quantum SVC, Pegasos: pegasos QSVC.

For "Salary," the BCP + PCA + QSVC model exhibited performance comparable to that of the BCP+PCA+SVC model, highlighting the effectiveness of QSVC even on limited data. The proposed

Table 3: Accuracy of the different models across different target variables.

	Target: CEO			
	SVC	BCP + PCA		
		+ SVC	+ QSVC	+ Pegasos
Acc	86	85	86	85
	Target: Salary			
Acc	73	60	59	56
	Target: Alumni Satisfaction			
Acc	86	81	81	81

SVC: support vector classifier; BCP + PCA + SVC: Proposed method with SVC, BCP + PCA + QSVC: Proposed method with QSVC, BCP + PCA + Pegasos QSVC: Proposed method with Pegasos QSVC

method with SVC and that with Pegasos QSVC yielded the same accuracy for "CEO" and "Alumni satisfaction." In particular, BCP + PCA + QSVC and BCP + PCA + SVC achieved 85% accuracy for predicting whether an alumnus would secure a high-level-management position and 81% accuracy for predicting whether an alumnus would choose to study at the university again.

5 CONCLUSIONS

This study demonstrated that quantum machine learning algorithms can achieve results comparable to those of classical ML algorithms when applied to reduced-dimensional educational data, addressing three key target variables: whether an alumnus secures a CEO position, alumni salary, and alumni satisfaction. These results are promising, as they confirm the feasibility of designing and implementing QML algorithms for practical applications in educational analytics despite current hardware limitations. The findings highlight the potential for QML methods, especially as quantum computing technology evolves.

Notably, while the accuracy of QML algorithms, such as QSVC, outperforms the 85% accuracy of their classical counterpart, SVC, for the CEO prediction task, no significant advantages in terms of computational efficiency were observed. However, this aligns with expectations given the current state of quantum hardware.

Future research will focus on addressing computational constraints and exploring quantum-native techniques such as quantum principal component analysis (QPCA). Incorporating QPCA into the proposed method has the potential to reduce dimensionality in a quantum framework, which could enhance the scalability of QML algorithms.

The findings of this research reinforce the relevance of QML for educational applications, with implications extending beyond this domain to other fields, such as social sciences, where complex data is prevalent.

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