Detection of Liver Diseases using Quantum Machine Learning

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ABSTRACT

Quantum Machine Learning (QML) merges the concepts of quantum computing with traditional machine learning (ML) to explore potential computational benefits in data processing and model performance. With the advent of Noisy Intermediate-Scale Quantum (NISQ) devices, hybrid quantum-classical strategies are becoming increasingly prominent, particularly in fields demanding high precision, such as healthcare. In this study, we investigate whether hybrid quantum computing can enhance certain aspects of classical ML—specifically, dataset balancing and the complexity of neural networks used during training. To this end, we use the Indian Liver Patient Dataset (ILPD) as a case study for liver disease detection. We introduce *QML-L*, a hybrid framework that effectively integrates classical and quantum ML methods, covering the full pipeline from data preprocessing to model architecture and parameter tuning. Our findings show that *QML-L* improves key performance indicators such as accuracy and precision, while reducing quantum resource requirements to a single qubit, thereby enhancing practical feasibility. These results highlight the promise of QML for medical diagnostics, especially within the constraints of NISQ-era technologies.

CCS CONCEPTS

• **Computing methodologies → Neural networks**; • **Computer systems organization → Quantum computing**.

KEYWORDS

Liver Diseases, Quantum Machine Learning, Quantum Computing, Machine Learning

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1 INTRODUCTION

Quantum Machine Learning combines quantum computing and classical machine learning to tackle complex challenges in data science with fewer data and computational resources [3]. In healthcare, traditional ML models like neural networks and decision trees have improved early diagnosis, but still struggle with imbalanced datasets and complex medical structures [2, 7, 8]. QML leverages quantum phenomena such as superposition and entanglement to learn from small, noisy, or unbalanced data, showing promise for tasks like disease classification, even on current NISQ devices [5, 6, 10]. Liver diseases are a major global health concern, causing around 2 million deaths annually [4], and current diagnostic methods are often invasive and error-prone, motivating the need for more efficient AI-based solutions.

This work presents a resource-efficient hybrid model with a single-qubit quantum layer, evaluated on the ILPD dataset and benchmarked against classical and quantum approaches.

2 METHODOLOGY

Our methodology, illustrated in Figure 1, includes dataset preparation, interfaces selection, hybrid model design, hyperparameter tuning, and performance evaluation.

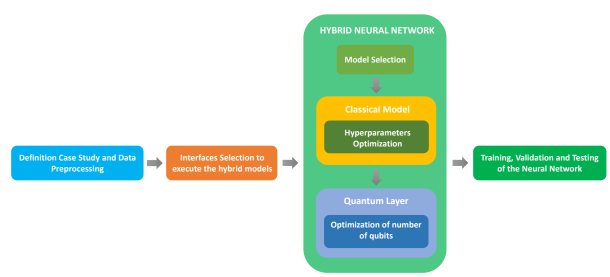

Figure 1: Diagram of this work project, illustrating the stages from left to right for training a neural network for classification using the ILPD dataset.

2.1 Dataset and Preprocessing

We used the ILPD from the UCI Repository[1], consisting of 583 records from India. It contains 10 features (e.g., total bilirubin, albumin, SGPT, SGOT) and a categorical variable ('Selector') indicating whether a patient has liver disease (416 positive, 167 negative).

To prepare the data for training, we applied dummy encoding, imputed missing values, recoded the target variable, performed train-test splitting, and standardized the features. These steps ensured consistent feature scaling and proper handling of categorical and missing data. Its important to notice that not balancing techniques were applied.

2.2 Proposed QML Model and Hyperparameter Tuning

The QML-L model is a sequential hybrid architecture tailored for NISQ-era quantum devices. It begins with an input layer (one neuron per feature), followed by a dense layer of 256 neurons with *ReLU* activation and *HeNormal* initialization. A dropout layer with a rate of 0.3 is included to mitigate overfitting. Next, a second dense layer with 128 neurons uses *ReLU* activation and *GlorotUniform* initialization. This is followed by a dense layer with one neuron, a quantum layer with a single qubit, and an output layer with a sigmoid activation function for binary classification. Figure 2 illustrates this hybrid quantum-classical structure.

To optimize performance, we combined *GridSearchCV* with manual tuning, adjusting key classical hyperparameters—such as learning rate, dropout, batch size, and early stopping—as well as quantum-specific settings (e.g., quantum data encoding techniques such as angle or amplitude encoding). The search strategy was informed by preliminary experiments and constrained by hardware limitations and training time. Model training was carried out using stratified 5-fold cross-validation.

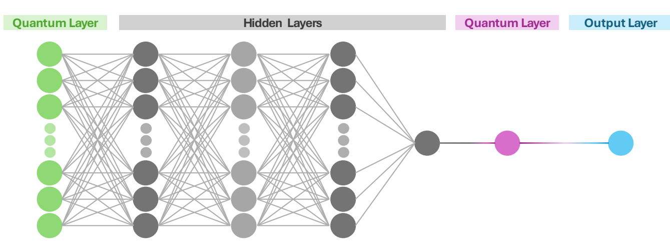

Figure 2: Structure of the hybrid *QML-L* model, showing classical layers, dropout, and the quantum layer.

3 RESULTS

We conducted an extensive review of state-of-the-art classical and quantum models for liver disease prediction. Among the classical approaches, the most competitive was the Stacking ensemble proposed in [1]. This method combines multiple classifiers—Random Forest, Decision Tree, XGBoost, and ExtraTrees—along with class balancing techniques, and achieved 90% across all performance metrics. However, it incurs a high computational cost due to the use of several resource-intensive models. In the quantum domain, we compared our model to the LR_QFE approach presented in [9], which employs Quantum Feature Engineering. While LR_QFE achieves a recall of 99%, its performance in the remaining metrics is lower (74% accuracy, 75% precision, and an F1-score of 85%) and it requires 10 qubits with a circuit delay of 40.

By contrast, our hybrid model, QML-L, provides a balanced trade-off between accuracy and efficiency. It achieves 83% accuracy, 80% precision, 90% recall, and an F1-score of 85%, while requiring only 1 qubit and a delay of 18, making it well-suited for implementation on current NISQ devices.

[1] https://archive.ics.uci.edu/dataset/225/ilpd+indian+liver+patient+dataset

4 CONCLUSIONS AND FUTURE WORK

This work presents QML-L, a hybrid quantum-classical model for liver disease detection. It achieves competitive performance while requiring minimal quantum resources, making it suitable for implementation on NISQ devices. Compared to state-of-the-art methods, QML-L offers a promising and efficient solution for medical diagnostics. Future work will focus on exploring improved quantum encoding techniques and advanced algorithms to further enhance its applicability and performance.

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