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Research Article

FedCarepod: Federated Quantum Transfer Learning Approach in Screening Process for Early Detection of Liver Abnormalities

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Abstract: The liver is the most frequently injured intra-abdominal organ that leads to complications. Visual interpretation depends on the expertise, and this justifies the need for automatic accelerated assistive prediction system. Classical and Quantum machine learning approaches are combined to leverage their benefits, and the feasibility of designing a novel system is explored. This approach successfully ends up with health care system for early detection and screening of liver diffused diseases to assist doctors and radiologists. The local model in each location uses quantum transfer learning and the learned neural parameters are transferred to the global model for update, and the aggregated parameters are used to update neural parameters by federated learning and communicated to local models. This learning approach is implemented using PennyLane. The detection performance is 99% using public liver dataset, hospital dataset and real time data from patients with updated model parameters. Due to the low cost and noninvasive nature, B mode ultrasound scanner is used. Amplitude encoding and optimizer reduces training time compared to classical approach and the result shows that this distributed Quantum approach is a promising research area if suitable Encoding and Ansatz circuit design is identified with cutting edge technologies. The proposed design outperforms the existing state-of-the-art techniques.

Keywords*:* Quantum Transfer Learning, Federated Learning, Variational Quantum Classifier, Liver Analysis, Early Survival Prediction

Introduction

Focal and Diffused liver diseases cause liver abnormalities and affect the texture of the liver tissues. Fatty and Cirrhosis is a group of chronic liver diseases in which normal liver cells are damaged. This is characterized by fibrosis and nodule formation. Sonographic appearance of the liver varies based on the causes. B scan ultrasound liver images are increasingly used in the diagnosis, characterization and grading of liver diseases and treatment planning due to its non-invasive nature and low cost.

Visual interpretation depends on the ability and expertise of the radiologist and physician. Expert knowledge has to be shared among practitioners for accurate diagnosis and making decisions for treatment planning. This justifies the need for an accurate diagnosis system that shows excellent performance comparable with radiologists.

To date, no fully automated diagnosis system exists that shows excellent performance comparable with experienced radiologist and hardware plus software implementation along the scanner machine (Provenzano et al., 2021; Rubin, 2019; Langlotz, 2019). Multiple devices like Siemen, GE, Philips, Toshiba, etc., data can be mixed for model building to learn scanner machine dependencies and build software for scanners. Experts' knowledge in terms of ground truth from more than one

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radiologist has to be transferred to model building approach. Innovations have to be introduced in machine learning models.

In this work, quantum machine learning is explored for liver disease diagnosis for the prediction about the liver status that assists in treatment planning. Sample normal and fatty liver images are given in Fig. 1(a) and Fig. 1(b).

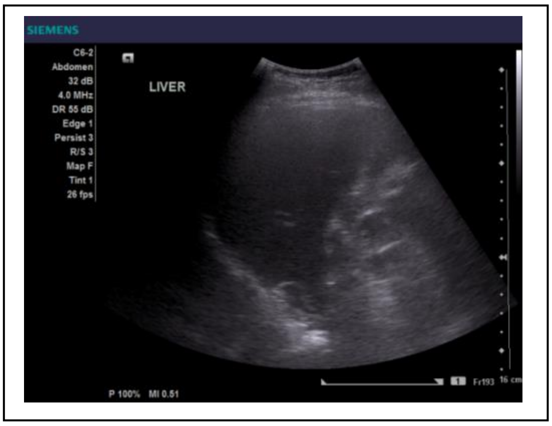

Fig. 1 (a): Normal Liver
(Courtesy: Devaki Scans and Diagnostics, Madurai)

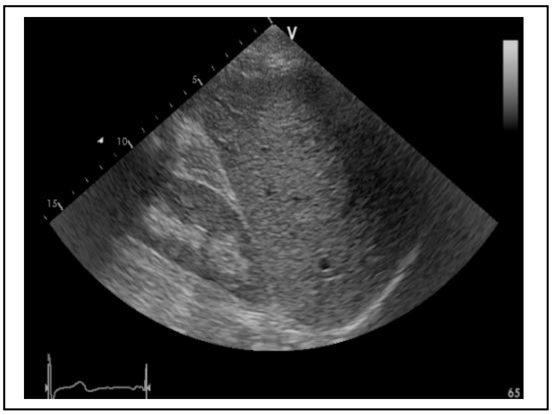

Fig. 1 (b): Fatty Liver *(Courtesy: Byra dataset)*

Literature Survey

Abnormality Diagnosis using Machine Learning (ML) Approach

In India, every year approximately 2.8% of adults are affected by liver diseases which present modest symptoms and are difficult to diagnose (Goyal et al., 2022). Survey indicates that the machine learning approach minimizes time and cost due to the knowledge transfer of experts in the form of hardware and software systems using high end servers and appropriate technologies. Various techniques and tuning of hyperparameters suggest that these techniques should be properly handled to enhance the accuracy of the model otherwise irrelevant to real world applications (Yadav H. S., and Singhal R.K, 2023; Alshagathrh & Househ, 2022).

Gupta et al., (2022) found that Logistic regression, Decision tree, Random Forest, KNNeighbor, Gradient Boosting, Extreme Gradient Boosting and LightGB yield good accuracy after feature selection for predicting liver patients. The work (Prakash & Saradha, 2022) used 52 features such as Gray Level Co-occurrence Matrix (GLCM) texture features, Gray Level Gradient Co-occurrence Matrix (GLGCM) texture features and Spearman's rank correlation for classification and prediction using Magnetic Resonance Imaging (MRI) and datasets. The predicted results are compared with existing methods and they show better results in terms of comparison parameters.

The accurate diagnosis of liver fibrosis ($\geq$ F2) with Chronic Liver Disease (CLD) is critical, as $\geq$ F2 is a crucial factor which should be considered in selecting an antiviral therapy for these patients. Liu et al., (2023) designed a Handcrafted-Feature-trained Deep Convolutional Neural Network (HFA-DCNN) that assists radiologists accurately diagnose liver fibrosis from ultrasound B mode images. The HFA-DCNN model employed attention features and handcrafted features in the back end of the model to give more accurate diagnosis of liver fibrosis and achieved accuracy, sensitivity, specificity, and area under the Receiver Operating Characteristic curve values of 0.863 (95% confidence interval (CI) 0.820–0.899), 0.879 (95% CI 0.823–0.920), 0.872 (95% CI 0.800–0.925), and 0.925 (95% CI 0.891–0.952), for the liver fibrosis patients.

Deep Learning based Approach using liver images

Lin et al., (2021) employed GoogLeNet (Inception-V1)-based deep learning architecture to classify Hepato Cellular Carcinoma (HCC) and Normal histopathology images to investigate and find the minimum number of annotated training images required to achieve a desired diagnostic accuracy. All experiments were performed on an NVIDIA GeForce GTX 1080 TI GPU.

Fatty liver image classification architecture based on a Convolutional Neural Network (CNN) with skip connection by combining shallow layer CNN with the differential image patches based on pixel level features was addressed by Zhu et al., (2022) to grade B scans liver images. The classification architecture classifies images as normal liver, low grade fatty liver, moderate grade fatty liver and severe fatty liver with an accuracy of 92%.

Ultrasound images are popularly known to contain speckle noise that degrades the quality of the images for interpretation. Hence, a study was carried out in

(Elamvazuthi et al., 2013) to reduce speckle noise using filtering algorithm such as Wiener, average, median, anisotropic diffusion and wavelets. Khan and Altalbe (2022) conducted an experimental study on 102 abdomen ultrasound images degraded by speckle noise and the analysis of 8 de-speckling filters, namely mean, median, kuan, lee, frost, adaptive homomorphic, wiener and anisotropic diffusion to find the optimum despeckling filter.

The purpose of the study in (Cheng & Malhi, 2016) is to evaluate the transfer learning with deep CNN for the classification of abdominal ultrasound images. They achieved 90.4% (1287/1423 images) to classify into 11 categories using VGGNet. The differences in classification accuracies between both neural networks and the radiologists were statistically significant. Doctors need to choose to narrow the field of view or reduce the scan line density to increase the penetration depth, but this affects the resolution and quality of the ultrasound imaging. To increase the resolution, Super Resolution Generative Adversarial Network (SRGAN) is used in (Ledig et al., 2017).

To address the dataset availability problem, a study (Tom & Debdoot Sheet, 2018) on synthetic simulated realistic pathological ultrasound images generated using Generative Adversarial Neural Network (GAN) was conducted. A novel liver fibrosis classification method (Meng et al., 2017) based on transfer learning and deep classifier FCNet is used to classify normal and four stages of liver fibrosis. Results show that accurate prediction models can be built but more training data requirement, image quality and experience are the limitations. For speckle noise removal, Lan and Zhang (2020) designed a new neural network based on U-Net named MARU network for denoising medical ultrasound images and achieved good performance.

Joo et al., (2023) build models trained using data from two, four and six machines and got an accuracy of 83.54%, 85.13% and 83.23% respectively in classifying no fibrosis, portal fibrosis, peripheral fibrosis, septal fibrosis, cirrhosis, 87.34%, 86.71% and 87.03% respectively in classifying no fibrosis, fibrosis, cirrhosis and found that deep learning model has not yet been trained to generalize enough to classify images acquired by the new machine.

Wang et al., (2021) surveyed deep learning in medical ultrasound image analysis and found the availability of a limited dataset and stated the importance and requirement of researcher and hospital cooperation to find efficient methods to implement computer aided diagnosis systems. Rassem et al., (2017) classify images based on Completed Local Ternary Pattern (CLTP) texture descriptor using the scene and medical image dataset. Fusing hand-crafted features with deep learning models resulted in good performance.

Survey indicates that the CNN is a good classifier which can be used for vision-based models. Dropout layer nullifies the contribution of certain neuron values to next layer while training with the dropout probability. This idea forces us to learn redundant patterns that are useful for better generalizations.

Skip connection technique bypasses some layers and directly connects to deeper or shallow layers. The cost associated with training CNN to get optimal model size, training time and memory requirements by preserving their performance is explored by Celaya et al., and PocketNet paradigm is proposed in (2023) for segmentation and classification tasks using MRI brain images and X rays of chest images. This a tiny lightweight CNN which is an appropriate choice for a memory and speed constrained environment.

Quantum Machine Learning (QML) Approach

Quantum technologies are powerful tools for a wide range of disciplines, including healthcare, due to exponentially growing computational power and advancement in machine learning algorithms. Furthermore, the processing of classical data and machine learning algorithms in the quantum area has given rise to an emerging field, quantum machine learning. Consequently, quantum machine learning is the most commonly used application of quantum computing.

The main objective of the work (Maheshwari et al., 2022) is to present a brief overview of current state-of-the-art published articles to identify, analyze, and classify the different QML algorithms and applications in the biomedical field. Furthermore, the approach complies with quantum machine learning models and quantum circuits using biomedical data to provide a broad overview of quantum machine learning limitations and future prospects.

Sofana Reka et al., (2024) extracted features from HAM10000 skin lesions dataset using MobilNet to build a Quantum Support Vector Classifier (QSVC) and achieved a classification accuracy of 72.5%. They designed a Quanvolutional Neural network which exhibits Quantum convolutional process with RY rotations and Pauli Z gates. This layer is followed by a classical convolutional layer along with softmax activation function. This combination yields an accuracy of 82.86%. This work on QML models reveals their potential for breakthroughs by integrating quantum hardware, enhancing existing medical systems and diagnostic capabilities.

Vijayakumar (2023) leveraged transfer learning with a hybrid quantum neural network and accelerated the training process which improved the accuracy and precision of the resulting models. This work assists radiologists to reduce time in the classification of Hepatitis C Virus (HCV) related liver lesions.

Yano et al., (2021) introduced Quantum Random Access Coding (QRAC) to map classical features to quantum enhanced feature space. This mapping limited the number of qubits for the Variational Quantum Classification (VQC) method and thereby speeds up the training process.

Maheshwari et al., (2022) explored quantum enhanced feature space. It was proved that the amplitude encoding based VQC achieved better accuracy compared to the VQC model when experimented with synthetic, sonar and diabetic datasets. Hence quantum state preparation is critical and active research (Haylicek et al., 2019) to be done in encoding part to yield accurate results. Also, the quantum model is to be optimized by updating the parameters using cost function as in a classical neural network. The Constrained Optimization by Linear Approximations (COBYLA) optimizer (Powell, 2007), is a good choice and used by many researchers.

Based on the literature survey, quantum machine learning is an active emerging technology to be explored further to improve disease diagnosis and early prediction in healthcare systems. The objective of this research is to understand the current trends in quantum machine learning and apply this to solve issues in liver disease prediction. Most studies say that classical machine learning is better and needs more contribution in quantum machine learning to face today's challenges in healthcare areas.

Research Methodology

The objective of this research is to answer the following questions:

1. What are the challenges and issues in quantum machine learning?
2. Is the availability of public data sets and promising results using QML approaches useful in designing healthcare systems?
3. Is it worth working on quantum machine learning in the future to come up with novel healthcare systems in early diagnosis?

and to solve the liver abnormality prediction problem as a case study in solving real world issues. Patient profile has male and female in all age groups. The image analyzed is an Ultrasound image. Patient data are collected from KGS Scan Centre and Devaki Scans and Diagnostics, Madurai for research purposes. The dataset preparation for this work is described below.

A total of 55 patients, 10 images from each patient, referred in (Byra et al., 2018; Rhyou & Yoo, 2021) is divided into two classes as normal and abnormal liver. Also to validate the federated QML approach, dataset was collected from KGS Scan Centre, Devaki Scans and Diagnostics, Madurai from 150 (75+75) normal patients and 250 (100 + 150) abnormal liver patients at different visits. The data is used for proposed model building, testing and comparison. For validating the system, different representative cases are needed from radiologist file. Hence the data pool is maintained in 3 sites to have enough number of diverse patient cohort to enhance the generalizability of the findings to broader population. Then median filtering is applied to remove noise because it preserves edges better as well as removes speckle noise. Region of Interest (ROI) is identified as in (Byra et al., 2018) and patches of size 100 x 100 are extracted without blood vessels. The data augmentation is done to balance the number of patches in each class for model building. 3000 patches are prepared in each class, named normal, and abnormal and the extracted sample patches are given in Fig. 2.

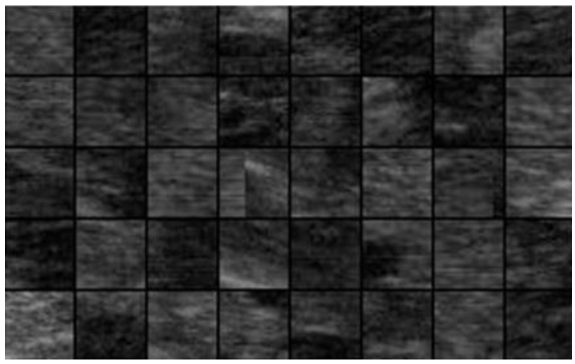

Fig. 2: Patches of Liver

The proposed approach uses the following quantum functionalities as described below.

a) Quantum State Preparation which maps patient attributes to Quantum States by Feature Mapping with Amplitude Encoding

b) Construction of Optimized Quantum Circuit and Measurement.

The function F maps input data x to the output label y. Objective is to improve the accuracy and minimize the loss.

Quantum State Preparation

Classical data is transformed to quantum data as in (1)

$$F_n = \{(|\psi_1\rangle, y_1), \dots (|\psi_i\rangle, y_i), \dots, (|\psi_n\rangle, y_n)\} \mid \quad (1)$$

Where $|\psi_i\rangle \in C^{2^d}$, C is a complex number and

$y \in \{c1, c2, c3, c4\}$. Amplitude encoding is done using equation (2).

$$|\psi_x\rangle = \sum_{i=1}^{2^n} x_i |i\rangle \tag{2}$$

Where $|\psi\rangle \in$ Hilbert space(H) and $\sum_i |x_i|^2 = 1$.
Its parameterized circuit is constructed using the steps after normalizing variables.

1. Apply Hadamard gate on each qubit.
2. Apply, on each qubit i, a rotation $R_z(2x_i)$.
3. For each pair of elements $\{i,k\} \in \{1,\ldots,n\}$ with i<k, do the following
   a. Apply a CNOT gate targeting qubit k and controlled by qubit i.
   b. Apply, on qubit k, a rotation $R_z(2(\pi-x_i)(\pi-x_k))$
   c. Repeat steps 3a.

The resulting quantum state through feature map F then goes through a variational form V: a variational circuit dependent on some optimizable parameters Θ. The output is the result of a measurement operation.

Construction of Optimized Quantum Circuit

Variational forms follow a layered architecture. The tree tensor variational form with k + 1 layers can be applied on $n = 2^k$ qubits. Each layer has half the number of parameters as the previous one, so the variational form relies on $2^k + {}^{2k-1} + \ldots + 1$ optimizable parameters of the form Θ_{rs}.

The procedure is:
Get k, Θ. On each qubit j, apply a rotation $Ry(\Theta_{0j})$
For all r = 1, …, k do
For all $s = 0,..2_{k-r-}$ 1 do
Apply a CNOT operation with target on qubit $1+s2^r$ and controlled by qubit $1 + s2^r + 2^{r-1}$. Apply a rotation $Ry(\Theta_{r,s})$ on qubit $1 + s2^r$.

The measurement operation used is the expected value of the first qubit as measured in the computational basis. The optimizer is used with specified iterations. Real Amplitude encoding and heuristic trail wave function used as Ansatz are chosen for implementation.

FedCarepod system ARCHITECTURE

The outline of the proposed Federated Quantum Transfer Learning (FQTL) approach is shown in Fig. 3. The approach consists of the following modules namely:

1. Quantum transfer learning - Local model
2. Model aggregation - Global model
3. Federated parameter update algorithm

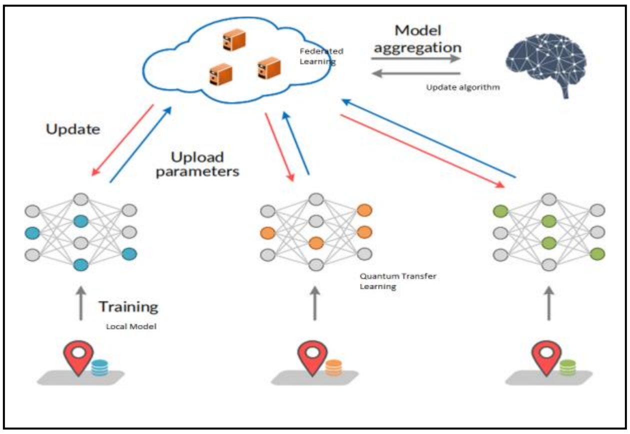

Fig. 3: FedCarepod System Architecture

Quantum Transfer Learning

The quantum transfer learning approach (Mari et al., 2020; Sasank Chilamkurthy, 2025) is implemented in open-source software framework PennyLane with necessary hyper parameters and required modifications (Fig. 4) for number of collaborating sites as 3.

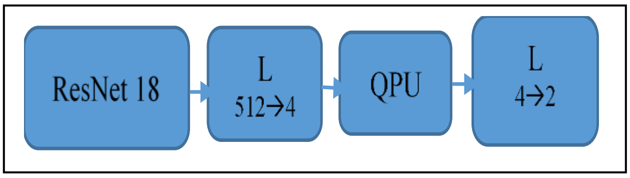

Fig. 4: Local Model

A Pretrained ResNet 18 model without fully connected layer is used with extracted 512 features. Then the training dataset with preprocessed patches are given as input for training. A Classical-Quantum transfer learning approach is adopted. 4 qubit dressed quantum circuit layer is concatenated and the weight parameters are trained. The cross entropy is the loss function which is minimized by Adam optimizer. Depth of quantum dressed circuit is 6 and epoch as 30, learning rate as 0.0004 are set and reduced after 10 epochs by a factor of 0.1 for updating. Input to local model is image patch and the output is the normal / abnormal.

Model Aggregation

The parameters trained in three local models are communicated to the global model for aggregation. Each parameter in different layers is aggregated by FedAvg using neural computation in global model. Decentralised distributed computing approach is employed with privacy preservation because data is not transferred, only parameters are communicated.

Federated Update Algorithm

The pseudo code of the update algorithm is given in Fig. 5 and update values are reflected in the selected local model.

```
initialize global model pw_0

for each round rt = 1, 2, ..., RT do

        for each client k in parallel do

            pw_k^t = ClientUpdate(k, pw_{t-1})

        end for

        pw_t = sum_k (n_k / n) * pw_k^t


#Aggregate updates


end for

def ClientUpdate(k, w):

# Client k updates model w using its local data

for each local epoch do

        w = w - η * ∇L(w; D_k)

# Gradient descent on local data D_k

end for

return w
```

Fig. 5: Pseudocode for FedAvg ()

The Software used is the open-source software framework PennyLane and PyTorch. Qiskit runtime is provided by an IBM account. For hardware Google Colab, is used to access quantum devices.

FedCarepod Implementation Results and Discussion

The dataset shown in Fig. 2 as patches after ROI extraction without blood vessels and data augmentation considered for experimental evaluation are tabulated in Table 1.

Table 1: Dataset description.

Number of patches (images) in each category (3 sites)			
Normal class	Abnormal class	Training	Testing
3000	3000	2400	600

Initially, the experimental setup had three collaborating sites, each with mutually exclusive one third of dataset. Dataset is mapped to quantum representation (Mari et al., 2020). Local models are built in each site, and parameters are sent for model aggregation. Then FedAvg calculates global model parameters and update local model parameters.

FQTL Model is evaluated for various epochs and model built for 30 epochs with early stopping procedure. The results are tabulated in Table 2, Table 3 and compared with Quantum support Vector Classifier (QSVC) in Table 4. It is assumed that the communication cost between local and global models is negligible due to fast network connection availability. Evaluation depends on the ground truth given by radiologist.

Table 2: Performance OF FQTL- binary Classifier

No.	Model Building and Evaluation Performance			
	Phase	*Epochs*	*Loss*	*Accuracy*
1	Training	1	0.3951	0.9633
2	Validation	1	0.1824	0.9633
3	Training	30	0.2951	0.8860
4	Validation	30	0.0737	0.9981
5	Best Testing	-	0.07	0.9980

Table 3: Confusion matrix and performance metrics

Model Evaluation Performance – FQTL							
TP	*FP*	*FN*	*TN*	*Pre*	*Rec*	*F1*	*Acc*
599	1	2	598	99.8	99.7	99.7	99.8

Table 4: Performance Comparision with QSVC

No	Time taken for Training and Accuracy for Test Data		
	Classifier (2 classes)	*Time taken*	*Accuracy*
1	Quantum Support Vector Classifier (QSVC)	40 seconds	92%
2	Federated Quantum Transfer Learning (FQTL)	4 seconds	99.8%

Model evaluation metrics True Positive (TP), False Positive (FP), False Negative (FN), True Negative (TN), Precision (Pre), Recall (Rec), F1 Score (F1) and Accuracy (Acc) are tabulated in Table III for 600 normal and 600 abnormal image patches with data distribution and skew handling.

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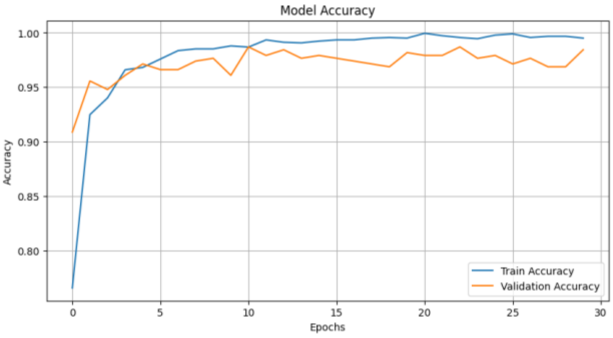

Fig. 6: ResNet Model Building Performance

ResNet-50, or Residual network with 50 layers, is a deep learning architecture designed to address the problem of vanishing gradients in very deep networks. Utilizing the skip connections, it allows the gradient to flow through the network without degradation, facilitating the training of deeper models.

To compare the QML approach and ML approach, the ResNet-50 architecture is used. Patch images are rescaled and ResNet-50 model built with train 80% and test 20% of data for evaluation (Fig. 6). After 10 epochs validation accuracy starts decreasing. Hence model is saved with 10 epochs training as per early stopping to avoid overfitting and 98% test accuracy is obtained. Performance metrics are given in Table 5.

Table 5: Confusion matrix and performance metrics

Model Evaluation Performance – TL – ResNet-50							
TP	*FP*	*FN*	*TN*	*Pre*	*Rec*	*F1*	*Acc*
591	9	15	585	98.5	97.5	98	98

Results analysis show that the QML approach is better compared to the classical ML approach. Hence, quantum is promising. Results shown are comparable with the state of the work reported in *(Byra et al., 2018; Rhyou & Yoo, 2021)*. Also works in (Maheshwari et al., 2022) are giving fruitful direction to QML for medical diagnosis and healthcare systems. Main challenges are Feature Map, Noise free quantum computer realization, Qubits Copy and Training time with iterations and accuracy.

In terms of computational feasibility, quantum computing is in an early stage and its real-world deployment for hospital settings with hardware and software deployment for clinical environments has to be analysed.

Major quantum computing companies, including IBM, Google, Microsoft, Rigetti, D-Wave, IonQ, Intel, and Amazon, have outlined roadmaps with varying approaches and timelines to achieving quantum advantage. This work uses IBM Qiskit and Google Colab facilities. TCS is at the forefront of integrating quantum computing in collaboration with IBM and the Government of Andhra Pradesh in India. Hence, there is a possibility of providing a developed system to hospitals to diagnose for early detection. After deployment in a clinical environment, global model parameters have to be updated using FedAvg and new cases across hospitals. The challenge lies in handling non-Independent and Identically Distributed (non-IID) data convergence across hospitals.

Qi et al., (2024) investigated federated learning by simulation with 2 sites. In their studies, they found that global data imbalance and local data heterogeneity influenced the learning outcome.

In this work a public dataset and two hospital datasets were used and investigated using 3 sites. Initially, the sites had 98.5% to 99.8% test accuracy and after first round with FedAvg of 3 sites parameters update, the global model achieved an accuracy of 99.8% which confirms the performance improvement for independent and identical class data distribution in all local models. For this experiment, datasets tabulated in Table I are used on three sites with mutually exclusive cases for local model building and global model update with two classes and an equal number of data samples.

For further comparative insights, the systematic approach used by Sheller et al. (2018) for training a model collaboratively without sharing the patient's data with hospitals is considered. Their approach used federated learning to preserve data privacy, but the proposed approach used quantum federated learning, which leverages their system by quantum computing. In the present circumstances, more solutions are available in the literature to handle non-IID or heterogeneous data which arises because of different sources of data, for example the scanner machine and protocol used. Pre-processing techniques can be used to make the data suitable for collaborative work with required homogeneous. When collaborative sites are leaving and new sites are entering, current global model parameter update can be notified to all participating sites. When parameters are shared by hospitals, the site may not respond if local model is not trained by new cases after deployment. This case is handled by FedAvg by changing number of local models for upload parameters (), number of trainable parameters and number of local models for update ().

Also, different researchers for example, Sheller et al. (2018) used different private datasets along with public datasets. Since the benchmark dataset is not available, under these circumstances, comparison cannot be made. It is necessary to have some common representation for non-IID, heterogeneous data to benchmark the solution approach. But, compared to ML approach, QML approach yields promising results. Hence in future design of healthcare system, QML approach can be used. To support the solution approach, comparative insights are tabulated in Table 6.

Table 6: Comparison with existing works

No	Comparative insights		
	Author and Year	*Classifier and Accuracy*	*Dataset and Diffused Liver disease Addressed*
1	Byra et al., 2018	CNN, 96.3%	Entire US image, 4 classes. Normal, fatty-mild, fatty-medium, fatty-severe
2	Rhyou and Yoo, 2021	Cascaded Neural network, 99.9%	Cropped image, 4 classes. Normal, fatty-mild, fatty-medium, fatty-severe
3	Zhu et al., 2022	CNN with skip connection, 92%	Image patches, 4 classes. Normal, fatty-low, fatty-moderate, fatty-severe
4	Celaya, et al., 2023	PocketNet, 99.9%	COVIDx8B, X ray images, Binary classes
5	Sheller et al. 2018	U-Net, 99%	Bra TS 2018, 3 tumor regions in brain diagnosed with gliomas
6	Luca Lusnig et al., 2024	Hybrid Quantum and FL, 97%	Hepatic Steatosis images, University of Trieste
7	Proposed System	Federated Quantum Transfer Learning, 99.8%	US image - Cropped image without blood vessels, 2 classes Normal and Abnormal

Proposed system contribution is in federated quantum transfer learning. Already patents are available with ML approach (Jae-chern Yoo, 2023). When we adopt FQML approach the advantages of quantum computing can be realized for real world applications. Instead of classical bits when qubits, exists in superposition of states are used for data representation, it allows to process and store more information exponentially than classical bits. Also, unique capability enables quantum devices much faster and more efficient due to the way it performs computation. This makes quantum machine learning approach powerful compared to machine learning approach. Federated learning preserves data privacy. Hence the proposed system outperforms other existing state of the techniques for liver disease detection.

The challenges to be addressed are special hardware requirement and environmental setup. This can be solved by cloud platform.

Recommended Research Direction

The recommendation for future research direction lies in data encoding method, aggregation scheme, model generalization to avoid overfitting, handling heterogeneous data or non-IID data and number of qubits to speed up performance for medical applications.

For quantum circuit to operate on classical dataset, encoding method is needed to transform the classical vector into a quantum state. In this work amplitude encoding is used. The basic idea behind encoding is to use the input values or transformation as rotation angles for the quantum rotation gate. Different encoding schemes can be proposed.

In this work, simple aggregation which calculates the average of parameters from each local model is used. In realistic situations, local machine (site) can upload corrupted model, or the quantum channel may introduce noise. To address these issues advanced aggregation schemes can be used.

Current quantum devices provide a smaller number of qubits in cloud platform. Future works can be done in this direction to overcome the issues for easy access by everyone. In this work we provide the framework to train hybrid classical-quantum classifier. This benefits the research in both privacy preserving AI and quantum AI and also shows a roadmap to build secure, reliable, collaborative and distributed quantum machine learning architecture.

In medical context, this kind of architecture needs organizational trust and multi-hospital data usage agreement protocols. Hence scalability of the framework towards large number is limited. This can be an active research area for the betterment of human lives.

Conclusion and Future Enhancements

Recent emerging field Quantum Machine Learning is explored to design health care systems. Based on the literature survey, more research is required on Feature Map, Ansatz circuit design and hyperparameter tuning. Results show that Federated Quantum Transfer Learning with Amplitude encoding and tree tensor variational form achieved an accuracy of 99.8% with 30 iterations for updating parameters through Adam optimizer. In the future, device can be designed with portable scanners with training time reduction and accuracy improvement. This work can be extended for other medical datasets like diabetes and retinopathy. Artificial intelligence powered doctor office can be realized.

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Ethics

Author adheres to ethical guidelines in all stages from planning, data collection to analysis. Avoided plagiarism, accurate in findings representation and acknowledge all contributions.

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