JOURNAL OF COMPUTER SCIENCE (ISSN NO: 1549-3636) VOLUME 18 ISSUE 01 JANUARY 2025

FedCarepod: Federated Quantum Transfer learning Approach for Early detection and Fast Screening of Liver abnormalities

Dr.K.Mala
Professor, Dept. of Computer Science and Engg.
Mepco Schlenk Engineering College
Sivakasi, India

0000-0003-2717-6404

***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 fused to get the benefits of both domain and the feasibility to design novel system is investigated. This approach successfully ends up with health care system for early detection and fast 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 Penny lane. The detection performance is 99% on public liver dataset and real time hospital dataset. 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 art techniques.**

Keywords—quantum transfer learning, federated learning, variational quantum classifier, liver analysis, early survival prediction

I. INTRODUCTION

Focal and Diffused liver diseases cause liver abnormalities and affect 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 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. The expert knowledge has to be shared among practitioners for accurate diagnosis and making decisions for treatment planning. This justifies the need for accurate diagnosis system that shows excellent performance comparable with radiologist.

Till date there is no perfect automatic diagnosis system that shows excellent performance comparable with experienced radiologist and hardware plus software implementation along with scanner machine. Multiple devices like Siemen, GE, Philips, Toshiba, etc., data can be mixed for model building. Experts knowledge 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 1(b).

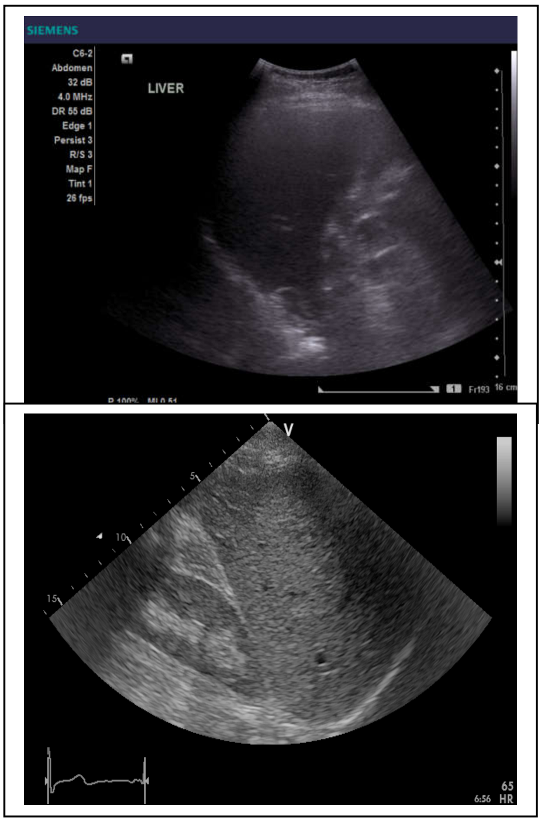

Fig. 1(a) Normal Liver
(Courtesy: Devaki Scans and Diagnostics, Madurai)
Fig. 1(b) Fatty Liver
(Courtesy: Byra dataset)

The rest of the paper is organized as follows: Section II outlines the related works in machine learning done for medical image analysis. Section III portrays the Research question and the functionalities used. Section IV discusses FedCarepod system implementation and the results with discussion. Section V concludes the work along with direction for future research.

II. LITERATURE SURVEY

A. Abnormality Diagnosis using Machine Learning (ML) Approach

In India, every year approximately 2.8% of adults are affected by liver diseases which presents modest symptoms and difficult to diagnose [1]. 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 system 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 [2].

Gupta, Ketan et. al. found that [3] 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 [4] used 52 features such as Gray Level Co-occurrence Matrix (GLCM) texture features, Gray Level Gradient Co-occurrence Matrix (GLGCM) and Spearman's rank correlation for classification and prediction using MRI images and datasets. The predicted results are compared with existing dominated methods and it shows 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. Z. Liu et al., [5] 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.

B. Deep Learning based Approach using liver images

Y. S. Lin, P-H. Huang and Y. Y. Chen [6] employed GoogLeNet (Inception-V1)-based deep learning architecture to classify Hepato Cellular Carcinoma (HCC) and Normal histopathology images to investigate and found 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 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 Haijiang Zhu et al. [7] 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 in [8], a study was carried out to reduce speckle noise using filtering algorithm such as wiener, average, median, anisotropic diffusion and wavelets. Muhammad Nasir Khan and Ali Altalble [9] conducted 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 [10] 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 US imaging. To increase the resolution, Super Resolution Generative Adversarial Network (SRGAN) is used in [11].

To address the dataset availability problem, a study [12] on synthetic simulated realistic pathological US images generated using Generative Adversarial Neural Network was conducted. A novel liver fibrosis classification method [13] based on transfer learning and deep classifier FCNetis 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 doctors experience are the limitations. For speckle noise removal, Lan and Zhang[14] designed a new neural network based on U-Net name MARU network for denoising medical US images and achieved good performance.

Y.Joo et al. [15] 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.

Y.Wang, et al. [16] surveyed deep learning in medical ultrasound image analysis and found the availability of limited dataset and stated the importance and requirement of researcher and hospital cooperation to find efficient methods to implement computer aided diagnosis system. Rassem, T.H., Khoo, B.E., Mohammed, M.F., and Makbol. N [17] classify images based on Completed Local Ternary Pattern (CLTP) texture descriptor using scene and medical image dataset. Fusing hand crafted features with deep learning models resulted in good performance.

The best results were obtained [18] for the combination of color and SURF extracted features fused with CNN model namely EfficientNet with an accuracy of 93.87%. Survey indicates that the CNN is a good classifier which can be used for vision-based model. Dropout layer nullifies the contribution of certain neuron values to next layer while training with the dropout probability. This idea forces to learn redundant patterns that are useful for better generalizations.

Skip connection technique bypass some layers and directly connect 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 Adrian Celaya et al. and PocketNet paradigm is proposed in [19] for segmentation and classification tasks using MRI brain images and X rays of chest images. This a tiny lightweight CNN which is appropriate choice for memory and speed constrained environment.

C. 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 [20] 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 the quantum machine learning models and quantum circuits using biomedical data to provide a broad overview of quantum machine learning limitations and future prospects.

S.S. Reka, H. L. Karthikeyan, A. J. Shakil, P. Venugopal and M. Muniraj [21] extracted features from HAM10000 skin lesions dataset using MobilNet to build 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 classical convolutional layer along with softmax activation function. This combination yields an accuracy of 82.86%. This work on QML models reveal their potential for breakthroughs by integrating quantum hardware, enhancing existing medical systems and diagnostic capabilities.

S.Vijayakumar [22] leveraged transfer learning with hybrid quantum neural network and accelerated the training process which improved the accuracy and precision of the resulting models. This work assist radiologist to reduce time in the classification of Hepatitis C Virus (HCV) related liver lesions.

H. Yano, Y. Suzuki, K. M. Itoh, R. Raymond and N. Yamamoto [23] introduced Quantum Random Access Coding (QRAC) to map the classical features to quantum enhanced feature space. This mapping limited the number of qubits for Variational Quantum Classification (VQC) method and thereby speed up the training process.

Maheshwari, D. Sierra-Sosa and B. Garcia-Zapirain [24] explored quantum enhanced feature space. It was proved that the amplitude encoding based VQC achieved better accuracy compared to VQC model when experimented with synthetic, sonar and diabetic dataset. Hence quantum state preparation is critical and active research [25] to be done in encoding part to yield accurate results. Also, quantum model is to be optimized by updating the parameters using cost function as in classical neural network. The Constrained Optimization by Linear Approximations (COBYLA) optimizer [26], 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 health care systems. The objective of this research work is to understand the current trends in quantum machine learning and apply this to solve issues in liver disease prediction. Most of the studies say that the classical machine learning is better and needs more contribution in quantum machine learning to face todays challenges in health care areas.

III. RESEARCH METHODOLOGY

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

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

and to solve the liver abnormality prediction problem as a case study in solving real world issue. The dataset preparation for this work is described below.

A total of 55 patients, referred in [27, 28] is used for proposed model building, testing and comparison. The data is divided into two classes as normal and abnormal liver. Also to validate the approach, dataset collected from KGS Scan Centre, Devaki Scans and Diagnostics, Madurai. Region of Interest (ROI) is identified as in [27] and patches are extracted. The data augmentation is done to balance the number of batches in each class for model building. 3000 patches are prepared and the extracted sample patches are given in Fig 2.

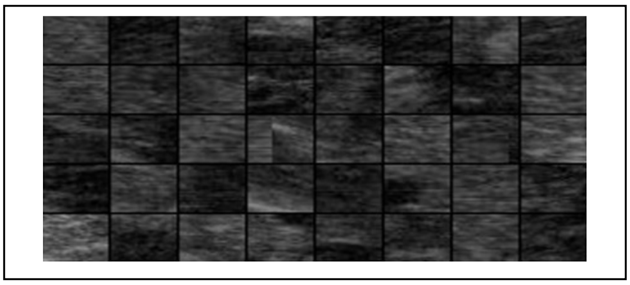

Fig. 2. Patches of Liver

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

a) Quantum State Preparation which maps patient attribute 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 output label y. Objective is to improve the accuracy and minimize the loss.

A. *Quantum State Preparation*

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

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

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

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

$$|\psi_x\rangle = \sum_{i=1}^{2^n} x_i|i\rangle \quad (2)$$

Where $|\psi\rangle$ € 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} Ɛ {1,...,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.

B. *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 $2^k + 2^{k-1} + \ldots + 1$ 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 Amplitudes encoding and heuristic trail wave function used as Ansatz are chosen for implementation.

IV. FEDCAREPOD SYSTEM IMPLEMENTATION

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

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

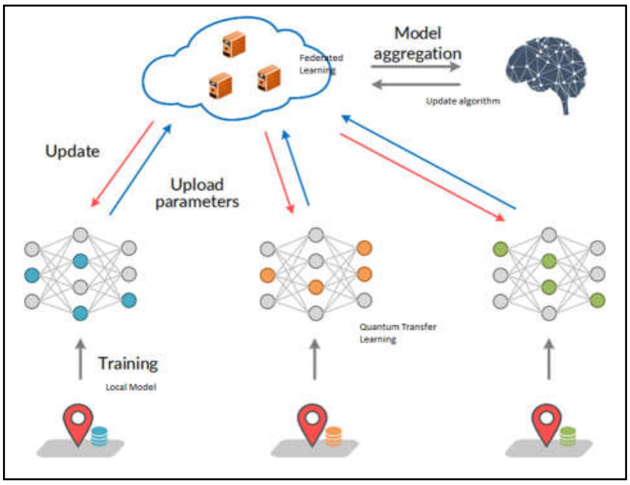

Fig. 3. FedCarepod system

A. *Quantum Transfer Learning*

The quantum transfer learning approach [29,30] is implemented in open source software framework Penny lane with necessary hyper parameters and required modifications. 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. 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 output is the normal / abnormal.

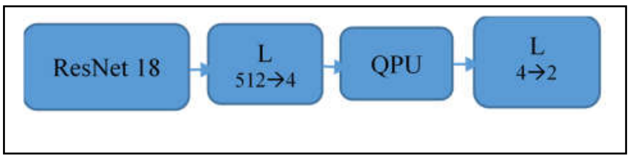

Fig. 4. Local Model

B. *Model Aggregation*

The parameters trained in local model is communicated to global model for aggregation. Each parameter in different layers are 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.

C. 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 results are tabulated in Table I and compared with Quantum support Vector Classifier (QSVC). It is assumed that the communication cost between local and global model is negligible due to fast network connection availability.

TABLE I. PERFORMANCE COMPARISION WITH QSVC

SNo	Time taken for Training and Accuracy for Test Data		
	Classifier (2 classes)	***Accuracy***	***Time taken***
1	Quantum Support Vector Classifier (QSVC)	92%	40 seconds
2	Federated Quantum Transfer Learning	99.8%	4 seconds

Results are analyzed. QML approach is better compared to classical ML approach.

Results shown are comparable with the state of the work reported in [27,28]. Also works in [20] are giving fruitful direction to QML for medical diagnosis and health care systems. Main challenges are in Feature Map, Noise free quantum computer realization, Qubits Copy and Training time with iterations and accuracy.

V. CONCLUSION AND FUTURE WORK

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 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.

ACKNOWLEDGMENT

The authors wish to thank the Management and Principal of Mepco Schlenk Engineering College (Autonomous), Sivakasi for the support in carrying out this research work. Also thank Devaki Scans and Diagnostics, KGS Scan centre, Madurai, Tamilnadu for their support in Dataset collection and knowledge transfer about disease diagnosis.

REFERENCES

[1] A. Goyal, A. Zafar, M. Kumar, S. B. R, T. B. K and J. Malik, "Cirrhosis Disease Classification by using Polynomial Feature and XGBoosting," 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2022, pp. 1-5, doi: 10.1109/ICCCNT54827.2022.9984293.

[2] H. S. Yadav and R. K. Singhal, "Classification and Prediction of Liver Disease Diagnosis Using Machine Learning Algorithms," *2023 2nd International Conference for Innovation in Technology (INOCON)*, Bangalore, India, 2023, pp. 1-6, doi: 10.1109/INOCON57975.2023.10101221.

[3] Gupta, Ketan & Jiwani, Nasmin & Afreen, Neda & D, Divyarani. (2022). "Liver Disease Prediction using Machine learning Classification Techniques", 2022, pp. 221-226. 10.1109/CSNT54456.2022.9787574.

[4] K. Prakash and S. Saradha, "A Deep Learning Approach for Classification and Prediction of Cirrhosis Liver: Non Alcoholic Fatty Liver Disease (NAFLD)," 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2022, pp. 1277-1284, doi: 10.1109/ICOEI53556.2022.9777239

[5] Z. Liu et al., "Automatic Diagnosis of Significant Liver Fibrosis From Ultrasound B-Mode Images Using a Handcrafted-Feature-Assisted Deep Convolutional Neural Network," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 10, pp. 4938-4949, Oct. 2023, doi: 10.1109/JBHI.2023.3295078.

[6] Y. S. Lin, P.-H. Huang and Y. Y. Chen, "Deep Learning-Based Hepatocellular Carcinoma Histopathology Image Classification: Accuracy Versus Training Dataset Size," in IEEE Access, vol. 9, pp. 33144-33157, 2021, doi: 10.1109/ACCESS.2021.3060765.

[7] HaijiangZhu ,Yutong Liu ,Xiaoyu Gao ,and Lei Zhang, " Combined CNN and Pixel Feature Image for Fatty Liver Ultrasound Image Classification", *Computational and Mathematical Methods in Medicine*, Hindawi, Vol. 2022, pp. 1-10.

[8] I.Elamvazulhi, M. L. B. M. Zain and K M Begam "Despeckling of ultrasound images of bone fracture using multiple filtering algorithms", *Mathematical and computer modellings*, 2013, Vol. 57, pp. 152-168

[9] Muhammad Nasir Khan, Ali Altalble "Experimental evaluation of filters used for removing speckle noise and enhancing ultrasound image quality", *Biomedical signal processing and control tool*, 2022, Vol. 73

[10] P.M.Cheng, H.S.Malhi, "Transfer Learning with Convolutional Neural Networks for Classification of Abdominal Ultrasound Images", *J Digital Imaging,* 2017, Vol. 30, pp. 234–243

[11] C.Ledig, L.Thesis, J.Totz, Z.Wang and W.Shi(2017) "Photo-realistic single image Super – resolution using a generative adversarial network", *Proc. IEEE Conference Comp. Vision Pattern Recognition (CVPR),* 2017, pp. 4681-4690.

[12] F.Tom and D.Sheet "Simulating patho-realistic ultrasound images using deep generative networks with adversarial learning", *Proc. IEEE 15th Int. Symp. Biomed. Imaging, (ISBI),* 2018, pp. 1174-1177.

[13] D.Meng, L.Zhang, G.Cao, W.Cao, G.Zhang and B.Hu, "Liver fibrosis classification based on transfer learning and FCNet for ultrasound images", *IEEE Access,2017,* Vol. 5, pp. 5804-5810.

[14] Y.Lan and X.Zhang "Realtime ultrasound image Despeckling using mixed-attention mechanism based residual UNet", *IEEE Access,* 2020, Vol. 8, pp. 195327-195340.

[15] Y.Joo, H.C.Park, O.J.Lee, C.Yoon, M.H.Choi and C.Choi "Classification of Liver fibrosis from Heterogeneous Ultrasound Image", *IEEE Access,* 2023, Vol. 11, pp. 9920-9930.

[16] Y.Wang, X.Ge, H.Ma, S.Qi, G.Zhang and Y.Yao, "Deep learning in Medical ultrasound Image Analysis: A Review", *IEEE Access,* 2021, Vol. 9, pp. 54310-54324.

[17] Rassem, T.H., Khoo, B.E., Mohammed, M.F., and Makbol. N, "Medical Scene and Event Image category Recognition using Completed Local Ternary Patterns (CLTP), *Malaysian Journal of Computer Science*, 2017, vol. 30, no. 3, pp. 200-218

[18] Basavaraj S Anami, Chetan V Sagarnal "A Fusion of hand-crafted features and Deep Neural Network for Indoor Scene Classification", *Malaysian Journal of Computer Science*, 2023, Vol. 36, No. 2, pp. 193-207

[19] Adrian Celaya , Jonas A. Actor, RajarajesawariMuthusivarajan, Evan Gates,Caroline Chung, DawidSchellingerhout Beatrice Riviere , and David Fuentes, "PocketNet: A Smaller Neural Network forMedical Image Analysis", *IEEE Transactions on Medical Imaging*, 2023, Vol. 42, No. 4

[20] D. Maheshwari, B. Garcia-Zapirain and D. Sierra-Sosa, "Quantum Machine Learning Applications in the Biomedical Domain: A Systematic Review," in *IEEE Access*, vol. 10, pp. 80463-80484, 2022, doi: 10.1109/ACCESS.2022.3195044

[21] S.S. Reka, H. L. Karthikeyan, A. J. Shakil, P. Venugopal and M. Muniraj, "Exploring Quantum Machine Learning for Enhanced Skin Lesion Classification: A Comparative Study of Implementation Methods," in IEEE Access, vol. 12, pp. 104568-104584, 2024, doi: 10.1109/ACCESS.2024.3434681

[22] S. Vijayakumar, "A Hybrid QNN-Based Framework for Accurate Early Detection of HCV Liver Abnormalities from CT Scans Using Custom Transfer Learning and AI Edge Device," 2023 IEEE Region 10 Symposium (TENSYMP), Canberra, Australia, 2023, pp. 1-5, doi: 10.1109/TENSYMP55890.2023.10223624.

[23] H. Yano, Y. Suzuki, K. M. Itoh, R. Raymond and N. Yamamoto, "Efficient Discrete Feature Encoding for Variational Quantum Classifier," in IEEE Transactions on Quantum Engineering, vol. 2, pp. 1-14, 2021, Art no. 3103214, doi: 10.1109/TQE.2021.3103050.

[24] D. Maheshwari, D. Sierra-Sosa and B. Garcia-Zapirain, "Variational Quantum Classifier for Binary Classification: Real vs Synthetic Dataset," in IEEE Access, vol. 10, pp. 3705-3715, 2022, doi: 10.1109/ACCESS.2021.3139323.

[25] V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, ''Supervised learning with quantum-enhanced feature spaces,'' Nature, vol. 567, no. 7747, pp. 209–212, Mar. 2019.

[26] M. J. D. Powell, ''A view of algorithms for optimization without derivatives,'' Math. Today-Bull. Inst., vol. 43, no. 5, pp. 1–12, 2007.

[27] M.Byra, G. Styczynsk,C. Szmigielski, P. Kalinowski, L.Michalowski, R.Paluszkeewcz Ziarkiew, "A transfer learning with deep convolution neural network for liver steatosis assessment in ultrasound images", Int. J. Comp. Assist Radio. Surg. Vol 13, pp 1895 -1903, 2018.

[28] Rhyou, Se-Yeol & Yoo, Jae Chern. "Cascaded Deep Learning Neural Network for Automated Liver Steatosis Diagnosis Using Ultrasound Images", Sensors 2021. (Basel, Switzerland). 21. 10.3390/s21165304.

[29] Andrea Mari, Thomas R. Bromley, Josh Izaac, Maria Schuld, and Nathan Killoran, "Transfer learning in hybrid classical quantum neural networks", Quantum Physics, Oct 2020.

[30] Sasank Chilamkurthy, PyTorch transfer learning tutorial. https://pytorch.org/tutorials/ beginner/transfer_learning_tutorial. html.