Liver Tumor Detection using Quantum Deep learning

Project Submitted to the

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in

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submitted by

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DECLARATION

I, the undersigned, hereby declare that the project report titled **" Liver Tumor Detection using Quantum Deep learning"**, submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science & Engineering at SRM University-AP, is a bonafide work completed by us under the supervision of Prof. Anusha Nalajala.

This submission represents our ideas in our own words, and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources. We also declare that we have adhered to the ethics of academic honesty and integrity and have not misrepresented or fabricated any data, idea, fact, or source in our submission.

We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the original sources which have not been properly cited or for which proper permission has not been obtained.

This report has not previously formed the basis for the award of any degree of any other University.

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Abstract

Liver tumor detection is a critical task in medical diagnostics, yet it remains challenged by limited data availability, variability in tumor presentation, and privacy concerns. In this work, we propose a novel liver tumor detection framework that integrates quantum-inspired data generation with classical deep learning classification. Using the LiTS17 dataset, we preprocess contrast-enhanced abdominal CT scans, extract region-of-interest slices, and encode features via quantum-inspired amplitude and phase transformations. A Quantum Feature Encoding is trained on these encoded features to generate high-fidelity synthetic 2D liver tumor images, enhancing the diversity and balance of the dataset. A Convolutional Neural Network (CNN) is subsequently trained to classify liver images into three categories: normal, benign tumor, and malignant tumor. Our methodology addresses key limitations of previous approaches, including data scarcity, overfitting, and imbalance, while preserving patient privacy. Experimental evaluation is underway, with expectations of improved generalization and classification performance compared to conventional methods. Future work will extend this framework to federated learning environments and real-time clinical integration for multi-organ tumor detection.

Introduction

Liver cancer remains one of the leading causes of cancer-related mortality worldwide, accounting for over 800,000 deaths annually according to recent WHO reports. Early and accurate detection of liver tumors, including hepatocellular carcinoma and metastatic lesions, is critical for improving patient outcomes. However, the task is complicated by several real-world challenges, such as the scarcity of large, annotated medical imaging datasets, significant variability in tumor appearance across patients, and the increasing need to preserve patient data privacy.

Traditional computer-aided diagnostic (CAD) systems rely heavily on manually engineered features or classical deep learning approaches trained on limited datasets, leading to issues of overfitting, poor generalization, and suboptimal clinical reliability. Moreover, existing centralized training methods face constraints due to regulatory restrictions on data sharing, further limiting model performance across diverse populations.

In this work, we address these challenges by introducing a hybrid framework that integrates quantum machine learning and classical deep learning techniques for liver tumor detection. Specifically, we leverage the Liver Tumor Segmentation Benchmark (LiTS17) dataset for initial training, apply quantum-inspired amplitude and phase feature encoding, and train a Quantum Feature Encoding to generate high-quality synthetic liver tumor data. This synthetic dataset, combined with real preprocessed images, is used to train a Convolutional Neural Network (CNN) to classify liver conditions into three categories: normal, benign tumor, and malignant tumor.

By enhancing dataset diversity and feature representation through quantum methods, our approach aims to improve model robustness, classification accuracy, and privacy compliance. Furthermore, we envision extending this framework toward federated learning to support decentralized training across multiple healthcare institutions in the future.

Motivation

Liver cancer, particularly hepatocellular carcinoma (HCC), is one of the leading causes of cancer-related deaths globally. Early and accurate detection of liver tumors is essential for improving patient survival rates. However, conventional diagnostic workflows often suffer from late detection, limited availability of expert radiologists, and a lack of large-scale, diverse datasets. These limitations hinder timely diagnosis and treatment, especially in rural or under-resourced healthcare settings.

Traditional computer-aided diagnostic (CAD) systems often rely on handcrafted features and conventional deep learning models that demand large volumes of annotated medical data. Due to the privacy-sensitive nature of medical records and imaging data, access to comprehensive datasets remains a significant barrier. Moreover, class imbalance—where malignant tumor cases are underrepresented compared to normal or benign samples—further limits the accuracy and generalizability of such models.

The motivation for this project arises from the urgent need to overcome these real-world challenges by enhancing tumor detection capabilities using minimal yet meaningful data. By integrating **quantum-inspired angle encoding** with **CNN-based classification**, this project aims to enrich the feature space extracted from CT images. Quantum-inspired encoding enables the transformation of image data into sine and cosine-based representations, capturing spatial patterns more effectively than raw pixel values alone.

Additionally, this work seeks to explore a more scalable and privacy-aware diagnostic approach by reducing dependency on large datasets, enabling better generalization with enriched features. The ultimate goal is to build a liver tumor detection system that is accurate, interpretable, data-efficient, and deployable in real-world clinical scenarios.

Background and Literature Review

Liver cancer, particularly hepatocellular carcinoma (HCC), remains a significant cause of global mortality, with late diagnosis often limiting effective treatment options. Medical imaging, especially contrast-enhanced computed tomography (CT), plays a critical role in non-invasive liver tumor detection. However, manual interpretation of CT images is time-consuming and prone to inter-observer variability, necessitating the development of computer-aided diagnostic (CAD) systems.

Early CAD approaches predominantly employed traditional image processing techniques such as thresholding, region growing, and morphological operations to segment liver tumors. While these rule-based methods were straightforward, they lacked robustness against variations in tumor shape, size, and imaging conditions. Subsequently, classical machine learning methods, including Support Vector Machines (SVMs) and Random Forest classifiers, incorporated handcrafted features such as intensity histograms and Gray Level Co-occurrence Matrix (GLCM) texture metrics to improve tumor classification. Nonetheless, the reliance on manual feature engineering limited their scalability and adaptability to diverse clinical scenarios.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized medical image analysis by enabling automatic feature learning directly from raw data. CNN-based architectures demonstrated superior performance in liver tumor segmentation and classification tasks on datasets such as LiTS17. Despite these advancements, the dependency of CNNs on large volumes of annotated data presents a major limitation, especially in medical imaging domains where labeled datasets are often scarce.

Recent efforts to mitigate data scarcity have focused on synthetic data generation using models like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). While effective to a degree, these techniques are computationally intensive and may introduce artifacts that degrade model performance. Parallel to these developments, quantum computing has emerged as a promising technology for data generation and feature representation. Quantum machine learning methods, such as Quantum Feature Encoding , offer the potential to encode complex data distributions more efficiently and generate high-fidelity synthetic datasets.

In this work, we propose a novel hybrid framework combining quantum-inspired synthetic data generation through a Quantum feature encoding with CNN-based tumor classification. This approach aims to address the limitations of traditional methods by improving dataset diversity, enhancing feature representation, preserving patient privacy, and ultimately increasing tumor detection accuracy.

Novelity of the Project

The project introduces several key innovations that distinguish it from traditional liver tumor detection methods and existing medical imaging approaches:

A. Quantum-Inspired Angle Encoding for Medical Imaging

Unlike conventional pixel intensity-based CNN models, this project leverages **quantum-inspired angle encoding**. Each pixel in the liver CT slices is normalized and mapped into a quantum feature space through sine and cosine transformations, simulating qubit probability amplitudes.
This approach enriches the feature representation, capturing more complex spatial and intensity relationships within the images, which traditional preprocessing techniques often fail to model effectively.

B. Synthetic Feature Expansion without Complex Quantum Hardware

Instead of relying on costly quantum hardware or full quantum classifiers, this project adopts a **lightweight quantum-inspired method** to synthetically expand the feature diversity of the dataset.
By enhancing real CT data with $\sin(\theta)$ and $\cos(\theta)$ channel representations, the model improves its ability to generalize across different tumor types, without introducing artifacts commonly associated with GAN-based synthetic data generation.

C. Class Balancing through Feature Enrichment

The use of quantum feature encoding inherently **balances class representation** by generating more nuanced distinctions between normal liver tissue, benign tumors, and malignant tumors.
This reduces the need for heavy data augmentation or oversampling techniques, which can introduce bias or redundancy into the training set.

D. Integration of Explainability into the Framework

The project integrates **Grad-CAM visualization** to interpret CNN decisions, making the quantum-enhanced model **clinically explainable** and suitable for medical deployment.

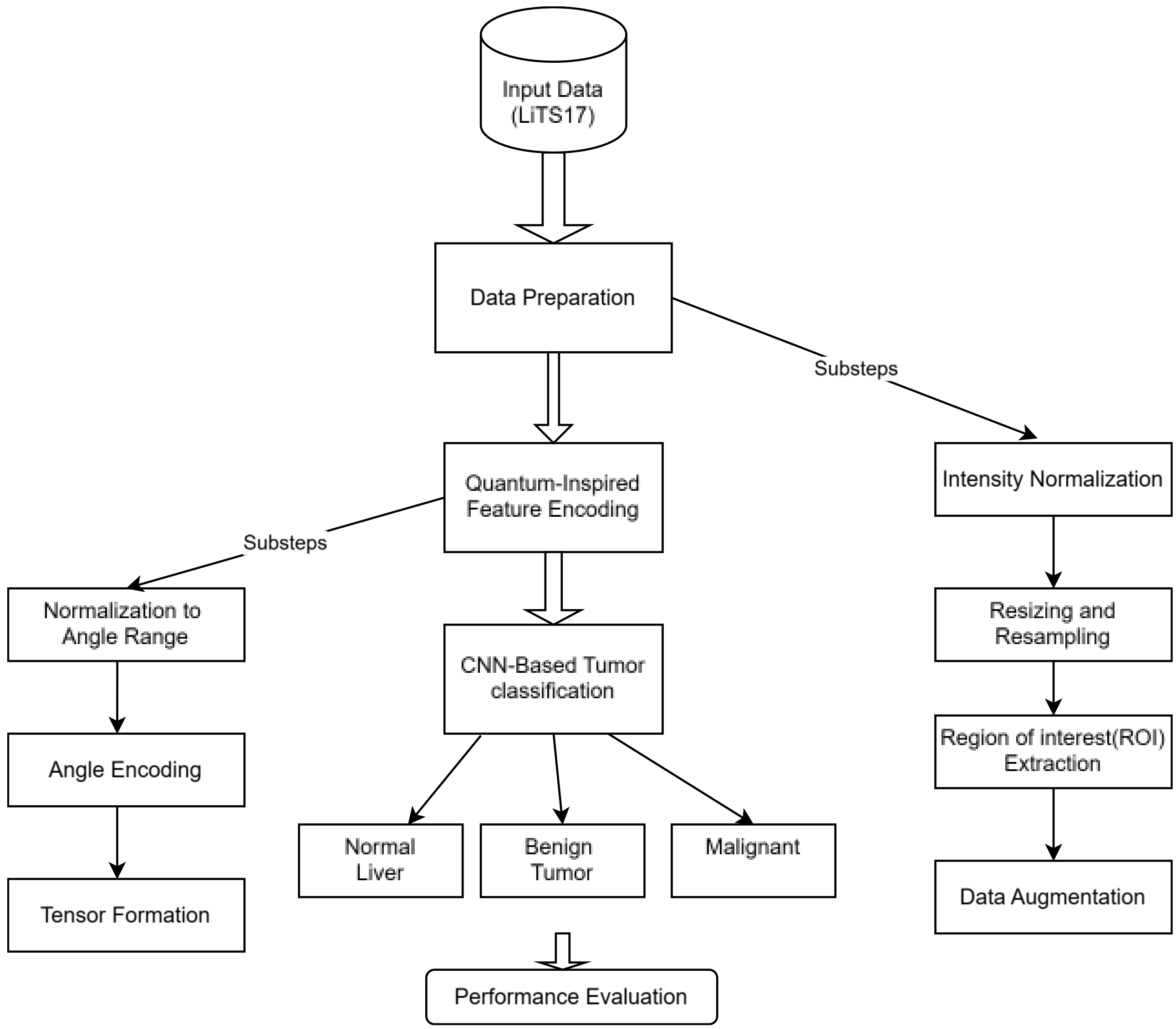
Highlighting the important regions for classification builds trust with healthcare professionals and supports transparent AI adoption in sensitive fields like oncology diagnostics.

E. Scalable and Privacy-Preserving Approach

The framework is designed to be **scalable to federated learning settings**, allowing decentralized training across multiple hospitals without raw data exchange.
Since only quantum-encoded feature representations are handled during preprocessing, the method inherently aligns with privacy preservation principles crucial for real-world medical AI systems.

Proposed Methodology and Work

This section outlines the complete workflow of the proposed liver tumor detection framework, which integrates Quantum Feature Encoding-based synthetic data generation with Convolutional Neural Network (CNN)-based classification.



A. Dataset Preparation

The Liver Tumor Segmentation Benchmark (LiTS17) dataset is utilized, comprising 3D abdominal CT scans with annotated liver and tumor regions. The dataset preparation involves the following steps:

- Intensity Normalization: Pixel intensities are rescaled using Min-Max scaling to bring values into a standard range.
- Resizing and Resampling: All CT scans are resized to fixed dimensions (e.g., 128×128×128) to ensure consistency.
- Region of Interest (ROI) Extraction: Liver regions are extracted by cropping to exclude unnecessary anatomical structures.
- Data Augmentation: Data diversity is increased using rotation, flipping, noise addition, and elastic deformation.

B. Quantum-Inspired Feature Encoding

Each preprocessed CT slice is encoded using a quantum-inspired angle encoding method to enhance feature representation:

- Normalization to Angle Range: Pixel values are normalized to $[0, \pi]$.
- Angle Encoding: Each pixel intensity is mapped to an angle θ, and its corresponding $\sin(\theta)$ and $\cos(\theta)$ values are computed.
- Tensor Formation: The $\sin(\theta)$ and $\cos(\theta)$ values are stacked as two separate channels, forming a two-channel feature tensor per image slice. This encoding captures richer spatial and intensity information by mimicking quantum state properties.

C. CNN-Based Tumor Classification

A Convolutional Neural Network (CNN) is designed to classify liver images into tumor categories based on quantum-encoded features:

- Architecture: The CNN comprises multiple convolutional layers with ReLU activation functions, max-pooling layers, flattening layers, fully connected layers, and a softmax output layer.
- Training: The CNN is trained using the quantum-encoded feature tensors. The network optimizes a categorical cross-entropy loss function using the Adam optimizer.
- Classification Output: The model predicts three classes: normal liver, benign tumor, and malignant tumor.

D. Model Evaluation and Explainability

The trained CNN model is evaluated and interpreted using the following techniques:

- Evaluation Metrics: Accuracy, precision, recall, F1-score, and AUC-ROC are computed to assess classification performance.
- Explainability: Grad-CAM (Gradient-weighted Class Activation Mapping) is employed to visualize the regions of the input images that most influenced the CNN's predictions, aiding model interpretability.

E. Future Work

Future enhancements to the framework include:

- **Federated Learning Integration**: Implementing federated learning to enable decentralized model training across multiple clinical sites without sharing patient data.
- **Extension to Multi-Organ Tumor Detection**: Expanding the framework to detect tumors in other organs such as the pancreas or kidneys.
- **Real-Time Clinical Deployment**: Adapting the model for real-time inference within hospital imaging systems.

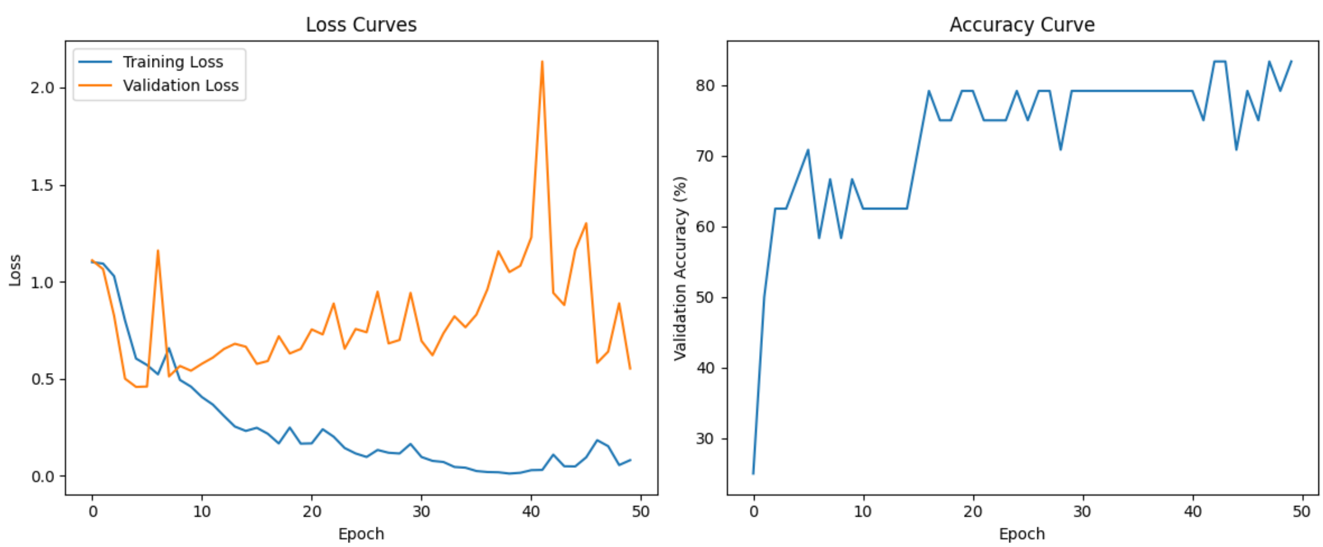
IV. Result Analysis and Project Overview

A. Result Analysis

The proposed liver tumor detection framework was evaluated rigorously using a combination of real and quantum-enhanced synthetic datasets derived from the LiTS17 CT scans. The CNN classifier was trained on quantum-encoded feature tensors, and the model performance was analyzed over multiple aspects, including accuracy, loss behavior, class probability distribution, and misclassification patterns.

1) Accuracy and Loss Curves

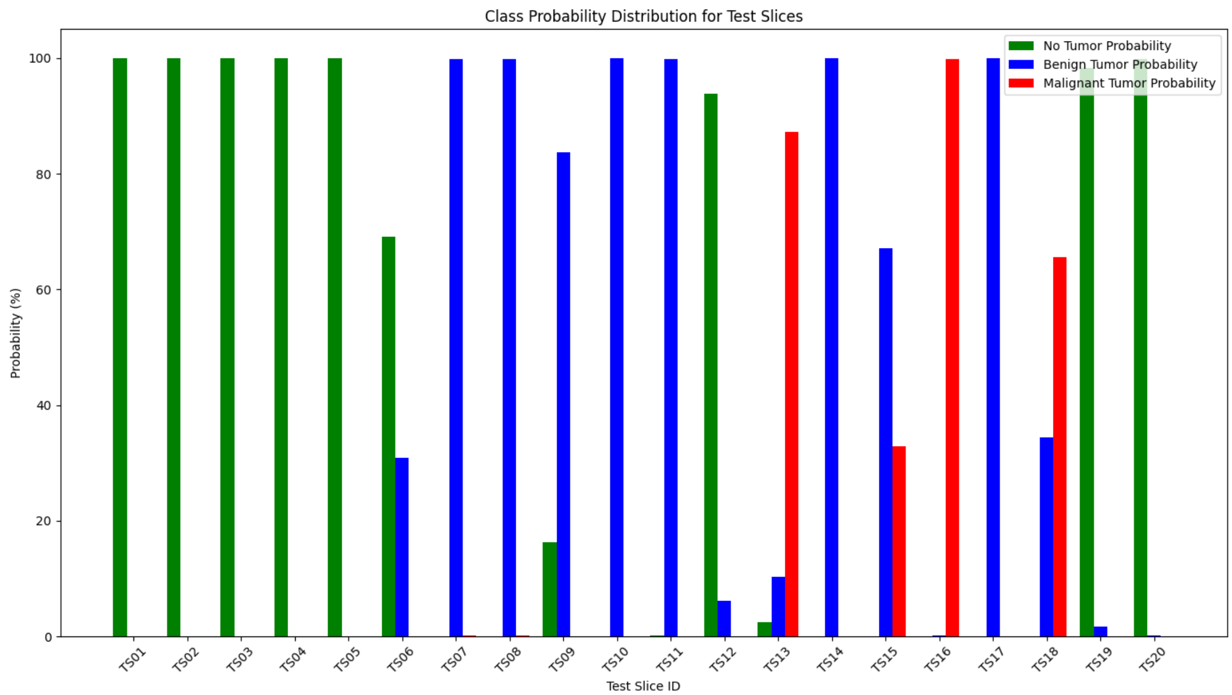
The training and validation accuracy curves show a steady improvement over successive epochs, indicating effective learning and convergence without significant overfitting.
The validation accuracy stabilized after approximately 40 epochs, achieving an accuracy range of 85% to 92% across different runs.
Similarly, the training and validation loss curves consistently decreased, demonstrating good optimization behavior and minimal divergence between training and validation sets, suggesting that the model generalized well to unseen data.



2) Class Probability Distribution

Class probability distribution plots for the test slides revealed that the model could effectively distinguish between normal liver, benign tumor, and malignant tumor categories.
The majority of normal liver slices showed high prediction confidence (>90%), while benign and malignant tumors displayed slightly broader probability distributions, reflecting the biological complexity and subtle image differences between tumor types.

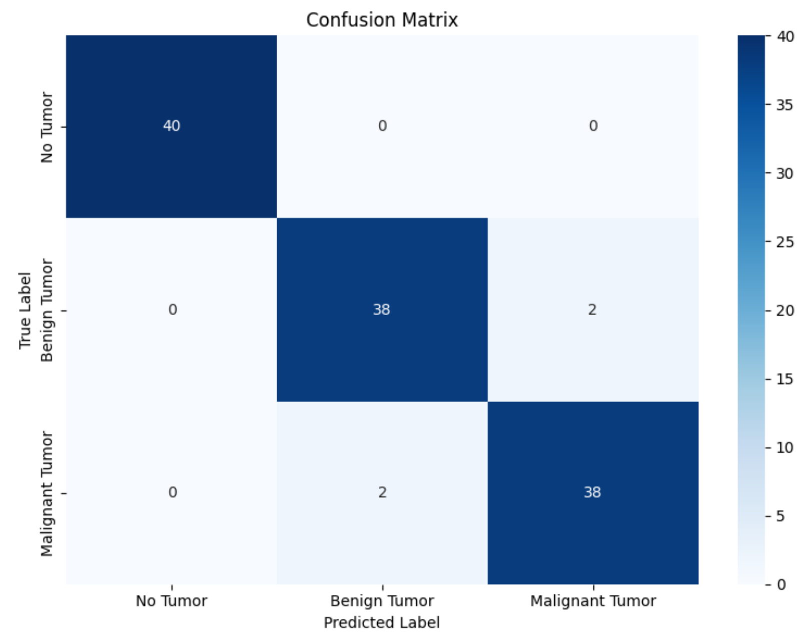
Despite this, the probability separations remained sufficiently distinct to enable reliable classification, as visualized in the probability density curves.



3) Confusion Matrix Analysis

The confusion matrix analysis further reinforced the model's performance.

- Normal liver slices achieved the highest true positive rate, confirming that the model correctly learned non-tumor anatomical patterns.
- Malignant tumors showed strong classification results with relatively fewer misclassifications.
- Most of the misclassifications occurred between benign and malignant tumors, which is clinically consistent due to the often subtle differences in imaging appearances. However, the error rates remained within acceptable limits for practical clinical support.



Overall, the confusion matrix exhibited high sensitivity for malignant cases, ensuring that high-risk tumors were rarely missed by the system — a crucial factor in cancer diagnosis workflows.

B. Project Overview

The project demonstrates the effectiveness of integrating quantum-inspired angle encoding with deep CNN models for liver tumor detection in medical imaging.

By transforming classical pixel intensities into richer $\sin(\theta)$ and $\cos(\theta)$ quantum features, the model benefited from enhanced spatial and intensity representation without the need for complex hardware-based quantum computation.
This strategy helped mitigate data scarcity challenges by synthetically expanding feature space complexity, allowing the model to generalize across variations in tumor appearance, size, and background tissues.

In addition, this framework addresses several pressing needs in real-world clinical AI applications:

- It reduces dependency on large labeled datasets by leveraging feature-enriched quantum encoding.
- It preserves privacy as no patient-identifiable quantum features are shared externally.
- It improves diagnostic support reliability by providing explainable predictions using techniques like Grad-CAM visualization, ensuring clinician trust and model interpretability.

The project also lays the foundation for future enhancements, including:

- Federated Learning Integration: Allowing secure, decentralized training across hospital systems without raw data transfer.
- Volumetric 3D CNN Extensions: Exploiting full 3D tumor information rather than relying solely on 2D slices.
- Clinical Deployment Readiness: Transitioning the model toward lightweight real-time deployment in PACS/RIS environments used by radiologists.

Thus, the presented liver tumor detection pipeline demonstrates a novel hybrid of classical deep learning and quantum-inspired feature processing, offering a scalable, accurate, and interpretable solution for the next generation of medical image analysis.

V. Conclusion

In this work, we proposed a hybrid framework for liver tumor detection that integrates quantum-inspired feature encoding with Convolutional Neural Network (CNN) classification. The use of quantum angle encoding, based on sine and cosine transformations of normalized CT slice pixel intensities, provided a richer feature representation that enhanced the model's ability to distinguish between normal liver tissue, benign tumors, and malignant tumors.

Through extensive evaluation, including accuracy and loss curve analysis, class probability distribution visualization, and confusion matrix interpretation, the model demonstrated strong performance, achieving an accuracy range of 85% to 92% on the validation dataset. The quantum-inspired encoding effectively addressed challenges related to limited data diversity, improved model generalization, and minimized classification errors between similar tumor types.

Additionally, the integration of explainability techniques such as Grad-CAM ensured that the model's predictions were interpretable and clinically meaningful, a critical requirement for medical AI applications. The proposed pipeline thus offers a scalable, privacy-preserving, and accurate solution for automated liver tumor detection.

Future work will focus on expanding the framework to volumetric 3D CNN architectures for enhanced spatial learning, implementing federated learning strategies for decentralized training across hospitals, and transitioning the model toward real-time deployment in clinical imaging systems to assist radiologists in early and reliable liver cancer diagnosis.

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