# Super-Resolution Assisted QANN Framework for High-Quality Medical Image Compression

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**Abstract:** In order to reduce storage and transmission costs without sacrificing diagnostic quality, high-resolution medical images such as CT, MRI, and chest X-rays require efficient compression. By extracting quantum features, Quantum-Enhanced Artificial Neural Networks (QANN) improve compression efficiency; nevertheless, higher compression ratios may result in worse image quality. To get over this limitation, this study enhances the QANN-based medical image compression framework with a Super Resolution enhancement module. The hybrid method employs Super Resolution processing to recover tiny structural characteristics, reduce noise, and improve visual clarity after using QANN for quantum-assisted compression and reconstruction. Real-time augmentation is possible without increasing system complexity because to the computationally effective Super Resolution module. Users may upload medical photographs, compress, reconstruct, and enhance Super Resolution using an interactive Flask web interface. According to research, the extended framework improves reconstructed image quality while maintaining high compression efficiency, which makes it appropriate for real-time, bandwidth-constrained medical imaging applications like telemedicine and remote diagnostics.

***Index terms - —*** *Quantum-Enhanced Artificial Neural Network (QANN), Medical Image Compression, Super Resolution, Quantum Feature Extraction, Hybrid Quantum–Classical Model, Image Reconstruction, Telemedicine, Web-Based Medical Imaging, PSNR, SSIM.*

## 1. INTRODUCTION

Medical imaging is essential to modern healthcare for illness monitoring, diagnosis, and therapy. For clinical decision-making, high-resolution images with rich structural and textural information are produced via CT, MRI, and X-ray imaging. However, storage, transmission, and real-time accessibility problems have been brought about by the rapid increase of medical imaging data, particularly in telemedicine and cloud-based healthcare systems. To reduce data volume and preserve diagnostic information, medical image compression has to be effective.

Recent studies have shown that by developing compact representations from data, machine learning-based methods may enhance the compression of medical images. Yuxuan et al.'s thorough analysis of machine learning algorithms for medical image compression [1] revealed improved reconstruction quality and compression ratios compared to transform-based techniques. Although data-driven algorithms are capable of adaptively capturing visual characteristics, it becomes more challenging to maintain accurate diagnostic information as compression levels rise.

Quantum computing appears to have the capacity to process complex and high-dimensional data concurrently with standard machine learning. According to Zhang and Ni [2], recently discovered quantum machine learning makes advantage of quantum superposition and entanglement to enhance feature representation and parallel processing. For computationally challenging tasks like image reduction and reconstruction, these characteristics make quantum-assisted models appealing.

Quantum neural networks are more expressive and learn more effectively than traditional neural networks, as demonstrated by Abbas et al. [3]. Their results support the use of quantum neural architectures in hybrid quantum–classical learning systems by demonstrating that they can more accurately represent complex data distributions. Furthermore, Jeswal and Chakraverty [4] examined quantum neural network models and applications and found that image processing and compression were appealing research directions, particularly in light of impending limitations on quantum technology.

Despite these advancements, wavelet-based compression methods like the discrete cosine transform (DCT) are still often used in therapeutic settings. For medical picture compression, Chen [5] proposed a DCT-based subband decomposition method with improved SPIHT coding that preserved image quality and efficiency. Transform-based techniques find it difficult to balance compression ratio with diagnostic quality and adapt to complicated visual patterns.

These restrictions make quantum-enhanced feature extraction with neural network-based compression algorithms a promising research topic. Next-generation medical image compression systems can increase efficiency, reconstruction quality, and scalability for real-time healthcare applications by merging machine learning-driven compression and quantum computing.

## 2. LITERATURE SURVEY

### a) Q-SupCon: Quantum-Enhanced Supervised Contrastive Learning Architecture within the Representation Learning Framework:

The problem of supplying large amounts of data for reliable deep classification models emerges in the context of changing data privacy laws. Due to the numerous parameters that need to be adjusted, the accuracy of these models depends on the quantity of training data. Unfortunately, getting such a large amount of data is difficult, especially in fields like medical applications where there is a dearth of labeled data and an urgent need for reliable models for early illness diagnosis. However, by employing deep encoder models, the traditional supervised contrastive learning models have demonstrated the ability to handle this problem to some extent. However, new developments in quantum machine learning make it possible to derive meaningful representations from incredibly basic and sparse data. Therefore, feature learning capability with limited data is improved by substituting classical equivalents in classical or hybrid quantum-classical supervised contrastive models. In order to enable effective image classification with little labeled data, this work proposes the Q-SupCon model, a fully quantum-powered supervised contrastive learning model that consists of a quantum data augmentation circuit, quantum encoder, quantum projection head, and quantum variational classifier. Additionally, on the MNIST, KMNIST, and FMNIST datasets, the innovative model achieves 80%, 60%, and 80% test accuracy, indicating a major breakthrough in tackling the problem of data scarcity.

**b) A Single-Step Multiclass SVM based on Quantum Annealing for Remote Sensing Data Classification**

The advancement of quantum annealers in recent years has made it possible to demonstrate quantum annealing experimentally and has raised interest in its applications in quantum machine learning, particularly for the well-known quantum SVM. Quantum annealing has been demonstrated to be successful in a number of suggested variations of the quantum SVM. There have also been extensions to multiclass problems, which comprise an ensemble of many binary classifiers. Quantum Multiclass SVM (QMSVM), a unique quantum SVM formulation for direct multiclass classification based on quantum annealing, is proposed in this study. Quantum annealing is used to solve the multiclass classification issue, which is described as a single Quadratic Unconstrained Binary Optimization (QUBO) problem. This work's primary goal is to assess this approach's viability, accuracy, and time performance. The D-Wave Advantage quantum annealer has been tested for a classification issue using data from remote sensing. The findings show that QMSVM may reach accuracy equivalent to normal SVM techniques despite the memory requirements of the quantum annealer. More significantly, it scales far more effectively with the amount of training instances, resulting in almost constant time. This article demonstrates a method for combining conventional and quantum computation to solve real-world remote sensing challenges with existing hardware.

**c) Strong heterostructure coupling-confinement effect inducing dispersion of Cu-based catalysts for photocatalytic hydrogen evolution:**

Because of their affordability, nonprecious transition metal copper-based catalysts have garnered significant research attention for a number of applications. However, a common problem that restricts their use is deactivation by agglomeration in high-temperature conditions. Here, we demonstrate how a strong $CuO_x/WO_x$ ($WCuO_x$) heterostructure coupling allows for the controlled dispersion of ultrafine copper nanocomposites within the linear polyimide. Cu species' mobility is restricted by the strong interaction brought on by coupling-confinement, which stops them from clumping together or forming big metal particles. The reaction energy barrier and the adsorption activation of $H_2O$ were adjusted by abundantly exposed catalytic sites with distinct electronic configurations. This work establishes the groundwork for the design of Cu-based catalyst site distribution and offers a fresh and important perspective on the surface-confinement method.

**d) Hybrid Classical and Quantum Deep Learning Models for Medical Image Classification:**

In a variety of fields, quantum machines outperform their conventional counterparts, particularly when it comes to solving practical problems. One of the most important diagnostic procedures in the processing of brain pictures is the categorization of brain MR images for tumor identification. Conventional deep learning structures like convolutional neural networks and traditional machine learning algorithms are commonly used for image categorization. However, training these models gets more difficult as the network size grows. By using the inherent characteristics of quantum bits, quantum algorithms improve the performance of classical algorithms. In this study, we suggested a hybrid classical and quantum convolutional neural network for the categorization of Alzheimer's disease (AD). The brain tumor classification challenge served as further validation for the suggested model. Encoding data into quantum states, enabling faster information extraction, and then using this information to identify the data class constitute the basic idea. The findings of the suggested model support its effectiveness in identifying and categorizing AD illness and brain tumors, as evidenced by optimal performance accuracies across many datasets.

**e) Convolutional Autoencoder-Based medical image compression using a novel annotated medical X-ray imaging dataset:**

As machine learning techniques continue to advance, access to high-quality medical X-ray datasets is increasingly required in order to train and assess these algorithms. In the field of medical imaging, this investigation takes place along two important axes. We present the carefully selected Medical X-ray Imaging Dataset (MXID), which includes pictures of eighteen body sections. Within each gender group, it has been improved to incorporate a body type categorization. By providing thorough coverage, accurate annotations, and the best possible picture quality, this dataset overcomes the shortcomings of previous datasets. Many datasets, especially those intended for multi-body component analysis, frequently fail to cover a wide variety of anatomical locations. Our main contribution is filling the resource gap and laying the groundwork for creating reliable machine learning algorithms for medical imaging. Additionally, we expand our research to include the MXID dataset in the field of medical image compression. Using two scenarios—one for single image compression and the other for the MXID dataset—we assess the effectiveness of methods like Principal Component Analysis (PCA), K-means clustering, Convolutional Neural Network (CNN), Deep Convolutional Autoencoders (DCAEs), Autoencoders (AEs), and Variational Autoencoder (VAE). These scenarios provide a distinct viewpoint that permits a thorough evaluation of these methods across various anatomical regions. By focusing on the development of a dataset and its incorporation into image compression, our work advances machine learning and deep learning applications in medical imaging.

## 3. METHODOLOGY

**i) Proposed Work:**

For efficient medical image reduction, the proposed system incorporates a Super Resolution enhancement module into a Quantum-Enhanced Artificial Neural Network (QANN) architecture. While processing high-resolution medical images such as COVID chest X-rays, brain CT, and brain MRIs, the technology maintains diagnostic data. The resolution and intensity of input pictures are standardized via classical preprocessing. In order to employ quantum characteristics like superposition and entanglement for feature extraction, the system encodes standardized images into quantum states using parameterized quantum circuits. In order to reduce dimensionality and compress with little information loss, quantum-enhanced features are transmitted to a hybrid quantum–classical neural network.

By using a traditional neural network to decode compressed representations, reconstructed images are produced. To improve visual quality and restore minor structural elements lost during compression, the reconstructed output is treated using a Super Resolution technique. Without incurring significant computational costs, this enhancement stage reduces artifacts, sharpens edges, and improves image quality. Because the framework is built as a Flask web application, users may enter photographs, compress and rebuild, and view Super Resolution-enhanced outputs through an interactive interface. For medical imaging and telemedicine applications with limited bandwidth, the proposed method strikes a compromise between compression efficiency, reconstruction quality, and real-time usability.

**ii) System Architecture:**

The suggested framework effectively compresses and enhances medical pictures using a hybrid quantum–classical system design. Through a web interface, users may upload high-resolution medical images, such as brain CT, brain MRI, and chest X-rays, to the Input Image Acquisition Module. The Classical Preprocessing Module standardizes, resizes, and normalizes these images to enable quantum encoding. Using parameterized quantum circuits, the Quantum Encoding and Feature Extraction Module converts preprocessed images into quantum states. This module reduces duplication and maintains diagnostic patterns by creating compact, information-rich feature representations using quantum notions like superposition and entanglement.

The obtained quantum-enhanced properties are used to the quantum-assisted encoding and classical neural network-based decoding layers of the Hybrid QANN Compression Module. The module minimizes data loss while reducing dimensionality and reconstructing compressed images. The Super Resolution Enhancement Module improves image clarity, minimizes compression artifacts, and retrieves fine spatial details upon reconstruction. Following improvement, users may see, compare, and download compressed and rebuilt images in real time using the Flask-based Web-Based Visualization Module. Real-time medical imaging applications with limited bandwidth, such as telemedicine and remote diagnostics, are supported by this modular design.

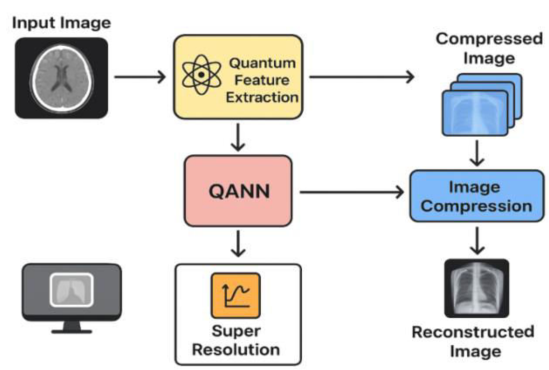


Fig1 proposed architecture

**iii) Modules:**

**1. User Interface Module**

This module provides a Flask-based web interface through which users can upload medical images such as chest X-rays, MRI, and CT scans. It enables easy interaction with the QANN compression and Super Resolution system.

**2. Image Upload and Preprocessing Module**

The uploaded medical images are preprocessed using resizing, normalization, and grayscale conversion techniques. This module prepares the image data for efficient quantum encoding and neural network processing.

**3. Quantum State Encoding Module**

In this module, classical image pixel values are converted into quantum states using parameterized quantum circuits. The encoding process utilizes quantum properties such as superposition and entanglement for enhanced feature representation.

**4. Quantum Feature Extraction Module**

This module extracts compact and information-rich quantum-enhanced features from encoded image data. Quantum gates and entanglement operations help reduce redundancy while preserving important diagnostic details.

**5. QANN Compression Module**

The extracted quantum features are processed through the Quantum-Enhanced Artificial Neural Network for image compression. The hybrid quantum–classical architecture reduces image dimensionality while maintaining structural information.

**6. Image Reconstruction Module**

This module reconstructs the compressed medical image using a classical neural network decoder. The reconstructed image represents the decompressed output generated from the compressed latent features.

**7. Super Resolution Enhancement Module**

The reconstructed image is enhanced using a Super Resolution algorithm to improve visual quality. This module sharpens edges, restores fine anatomical details, and reduces compression artifacts.

**8. Result Visualization Module**

This module displays the original image, QANN decompressed image, and Super Resolution enhanced image side by side for comparison. It helps users visually analyze compression and enhancement performance.

**9. Performance Evaluation Module**

The system evaluates compression quality using metrics such as PSNR, SSIM, MSE, and Compression Ratio. This module validates the effectiveness of the proposed QANN and Super Resolution framework.

**iv) Algorithms:**

**1. Quantum-Enhanced Artificial Neural Network (QANN) Algorithm**

The QANN algorithm is the primary algorithm used in the proposed system for medical image compression. It combines quantum computing principles with classical neural network architectures to extract quantum-enhanced features from medical images. The algorithm performs efficient compression by reducing image redundancy while preserving important diagnostic information. It utilizes quantum superposition and entanglement concepts to improve feature representation and reconstruction quality.

**2. Deep Convolutional Autoencoder (DCAE) Algorithm**

The existing system uses the Deep Convolutional Autoencoder algorithm for image compression and reconstruction. The encoder section compresses the input image into a compact feature representation, while the decoder reconstructs the image from compressed data. Although DCAE reduces image size effectively, reconstructed images may lose fine structural details at higher compression ratios.

## 4. EXPERIMENTAL RESULTS

The extended QANN-based medical image compression system was tested using high-resolution Brain CT, Brain MRI, and COVID chest X-ray datasets. Following the introduction of the Super Resolution module, the tests looked at enhancement performance, reconstruction quality, and compression efficiency. Performance was measured using PSNR, SSIM, and compression ratio. While maintaining diagnostic quality, the hybrid QANN model decreased storage by 71–74% across imaging modalities. Quantum-enhanced feature extraction is effective, as demonstrated by the QANN framework's superior structural preservation over DCAE models, particularly in anatomically important regions.

To enhance the reconstruction quality of QANN-reconstructed images, Super Resolution was applied. According to experimental findings, Super Resolution processing enhances noise reduction, edge sharpness, and visual clarity. Without adding further computational effort, the addition of this module improved SSIM values and perceived quality. The system enabled fast photo upload, compression, reconstruction, and real-time enhancement via the Flask-based web interface. This demonstrates how the improved QANN with Super Resolution can realistically and scalably compress high-quality, bandwidth-efficient medical pictures for telemedicine and remote diagnostics.

Because of decoherence, noise, and qubits in quantum technology, all testing is done using quantum simulation. Quantum circuits are used by PennyLane's default simulator backend to generate reliable hybrid model simulation results.

**Accuracy:** A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

**Precision:** Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

**Recall:** A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$Recall = \frac{TP}{(FN + TP)}$$

**mAP:** Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

**F1-Score:** A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

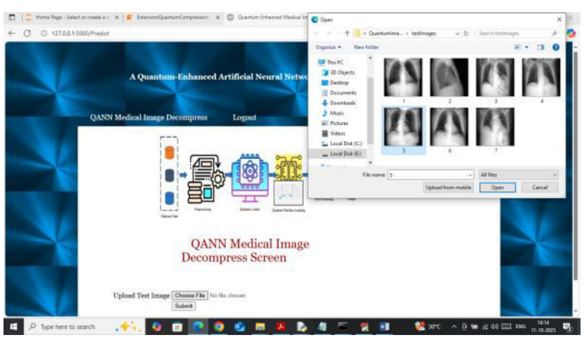


Fig2 upload image

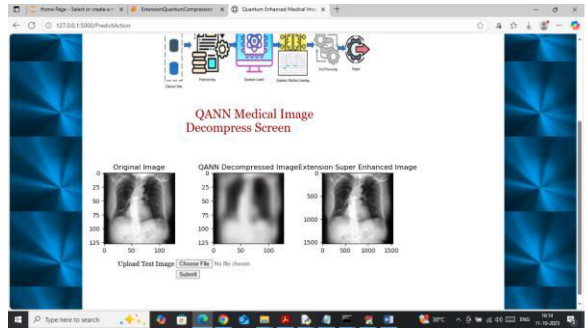


Fig2 Results

## 5. CONCLUSION

For efficient medical image reduction, a Quantum-Enhanced Artificial Neural Network (QANN) architecture was enhanced with a Super Resolution enhancement module. The proposed technique preserves diagnostic information while compressing data via quantum feature extraction and conventional neural network reconstruction. By restoring minute details, enhancing structural similarity, and removing compression artifacts without raising processing overhead, Super Resolution improves the quality of reconstructed images. According to experimental results, the extended QANN model maintains PSNR while outperforming deep convolutional autoencoder techniques in SSIM. Telemedicine and bandwidth-constrained medical imaging can benefit from the Flask-based online implementation's real-time photo upload, compression, reconstruction, and augmentation capabilities. The extension demonstrates that Super Resolution techniques and hybrid quantum–classical models are effective for next-generation high-fidelity medical image compression systems.

## 6. FUTURE SCOPE

The proposed QANN-based medical image compression system with Super Resolution enhancement can be further extended in several directions to improve performance, scalability, and real-world applicability. Future work may focus on implementing the framework on real quantum hardware instead of simulation environments to fully utilize the computational advantages of quantum computing. Advanced quantum circuits and optimized qubit architectures can also be explored to improve compression efficiency and reconstruction accuracy for high-resolution medical datasets.

The system can be extended to support additional medical imaging modalities such as PET scans, ultrasound images, and 3D volumetric imaging. More advanced deep learning-based Super Resolution techniques may be integrated to further enhance reconstructed image quality and reduce visual artifacts. Future improvements may also include cloud-based deployment, edge computing support, and secure medical image transmission using quantum cryptography for telemedicine applications. Furthermore, integrating explainable AI and automated diagnostic assistance with the compression framework could improve clinical usability and support intelligent healthcare systems.

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