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Research Paper

MedSR-QANN: A Next-Generation Framework for Intelligent Medical Image Compression

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Abstract:

The growing use of digital healthcare systems has led to a significant increase in the generation and transmission of high-resolution medical images, creating challenges in storage management and network bandwidth utilization. Efficient image compression techniques are therefore essential to reduce data size while preserving clinically relevant information. This study presents a hybrid medical image compression framework that combines Quantum-Enhanced Artificial Neural Networks (QANN) with a Super-Resolution (SR) enhancement module to improve reconstruction quality after compression. The QANN model is employed to learn compact feature representations and perform efficient image compression and reconstruction. To address the loss of fine anatomical details that may occur at higher compression levels, a Super-Resolution mechanism is integrated into the post-reconstruction stage. The SR module enhances image sharpness, restores subtle structural features, and suppresses reconstruction artifacts, resulting in improved visual and diagnostic quality. The proposed system is implemented through a user-friendly Flask-based web application that enables image upload, compression, reconstruction, and enhancement in a seamless workflow. Experimental evaluation demonstrates that the integration of Super-Resolution significantly improves reconstructed image quality while maintaining effective compression performance. The proposed framework offers a practical solution for medical image storage and transmission, making it particularly suitable for telemedicine, remote healthcare services, and other bandwidth-limited clinical environments.

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

1. INTRODUCTION

Medical imaging plays a vital role in modern healthcare by supporting disease diagnosis, treatment planning, and patient monitoring. Advanced imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and X-ray imaging generate high-resolution images containing detailed anatomical and pathological information. The increasing adoption of digital healthcare systems has led to a rapid growth in medical image data, creating significant challenges in terms of storage requirements, transmission bandwidth, and real-time accessibility. These challenges are particularly evident in telemedicine, cloud-based healthcare platforms, and remote diagnostic systems, where efficient image transmission is essential. Consequently, medical image compression has become a critical research area aimed at reducing data size while preserving diagnostic image quality.

Recent developments in machine learning have significantly improved the performance of medical image compression techniques. Data-driven models can learn compact feature representations directly from image data, enabling higher compression efficiency and better reconstruction quality compared to conventional approaches. A comprehensive review by Yuxuan et al. [1] highlighted the effectiveness of machine learning-based compression methods in achieving superior compression ratios while maintaining important visual characteristics. However, preserving fine anatomical details and diagnostic information remains a challenge when higher compression levels are applied.

The emergence of quantum computing has introduced new possibilities for handling complex and high-dimensional datasets. Quantum machine learning techniques exploit principles such as quantum superposition and entanglement to process information more efficiently than traditional computational methods. Zhang and Ni [2] demonstrated that quantum-enhanced learning models can improve feature representation and computational parallelism, making them suitable for image compression and reconstruction tasks. These capabilities offer promising opportunities for developing advanced medical image compression frameworks.

Quantum Neural Networks (QNNs) have attracted considerable attention due to their ability to model complex data distributions with enhanced learning capabilities. Abbas et al. [3] showed that quantum neural architectures can achieve higher representational power than conventional neural networks, making them effective for hybrid quantum-classical learning environments. Similarly, Jeswal and Chakraverty [4] emphasized the potential of quantum neural networks in image processing applications, identifying image compression as a promising research direction for future healthcare systems.

Despite these advancements, traditional transform-based methods such as the Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Set Partitioning in Hierarchical Trees (SPIHT) remain widely used in medical image compression. Chen [5] proposed an enhanced DCT-based subband decomposition approach combined with SPIHT coding, achieving efficient compression while maintaining acceptable image quality. Nevertheless, transform-based techniques often struggle to adapt to complex image structures and may fail to preserve subtle diagnostic details at high compression ratios.

To address these limitations, this work proposes a **Super-Resolution Assisted Quantum-Enhanced Artificial Neural Network (SR-QANN) Framework for High-Quality Medical Image Compression**. The proposed system integrates quantum-enhanced feature extraction with neural network-based compression and incorporates a Super-Resolution enhancement module to improve reconstructed image quality. The QANN component learns compact representations for efficient compression, while the Super-Resolution module restores fine structural details, reduces reconstruction artifacts, and enhances visual clarity after decompression. This hybrid approach aims to achieve a balance between compression efficiency and diagnostic image preservation. Furthermore, a Flask-based web application is developed to provide an interactive platform for image upload, compression, reconstruction, and enhancement. The proposed framework is designed to support real-time medical imaging applications, including telemedicine, cloud healthcare services, and remote diagnostics, where both image quality and transmission efficiency are of paramount importance..

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 CuOx/WOx (WCuOx) 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 H2O 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.

3. METHODOLOGY

i) Proposed Work:

The proposed system introduces a Super Resolution Assisted Quantum-Enhanced Artificial Neural Network (SR-QANN) framework for efficient medical image compression and reconstruction. The framework is designed to reduce storage and transmission requirements while preserving the diagnostic quality of medical images. It is particularly suitable for processing high-resolution medical imaging modalities such as COVID-19 Chest X-rays, Brain CT scans, and Brain MRI images, where maintaining critical anatomical information is essential for accurate diagnosis.

Initially, the input medical images undergo a preprocessing stage in which image dimensions, intensity values, and pixel distributions are normalized to ensure consistency across different datasets. This preprocessing step improves the stability and performance of subsequent quantum-enhanced learning operations. After normalization, the images are encoded into quantum states using parameterized quantum circuits (PQCs). The quantum encoding process exploits quantum mechanical properties such as superposition and entanglement, enabling the extraction of highly informative feature representations from complex medical image data.

The generated quantum feature representations are then provided to a hybrid Quantum-Enhanced Artificial Neural Network (QANN) that combines quantum feature learning with classical neural network processing. This hybrid architecture learns compact latent representations of the medical images, effectively reducing dimensionality and achieving high compression efficiency while minimizing information loss. The compressed feature vectors require significantly less storage space and transmission bandwidth compared to the original images.

During the reconstruction phase, the compressed representations are decoded through a classical neural network decoder to generate reconstructed medical images. Although the reconstruction process preserves most structural information, some fine details may be degraded due to compression. To address this limitation, a Super Resolution (SR) enhancement module is integrated into the framework. The Super Resolution model operates on the reconstructed images to recover high-frequency details, enhance image sharpness, restore subtle anatomical structures, and suppress compression-related artifacts. This enhancement stage significantly improves visual quality and diagnostic reliability without introducing substantial computational overhead.

The complete framework is implemented as a Flask-based web application, providing an interactive platform for medical image processing. Users can upload medical images, perform compression and reconstruction, and visualize the Super Resolution-enhanced outputs through a user-friendly interface. The system supports real-time operation, making it suitable for practical healthcare environments.

By integrating quantum-enhanced feature extraction, neural network-based compression, and Super Resolution reconstruction, the proposed SR-QANN framework achieves an effective balance between compression ratio, image quality, and computational efficiency. Consequently, it offers a promising solution for medical image storage, transmission, telemedicine services, cloud-based healthcare systems, and remote diagnostic applications where bandwidth and storage resources are limited.

ii) System Architecture:

The proposed Super Resolution Assisted Quantum-Enhanced Artificial Neural Network (SR-QANN) framework adopts a hybrid quantum–classical architecture for efficient medical image compression, reconstruction, and enhancement. The system is designed to process high-resolution medical images while preserving important diagnostic information and reducing storage and transmission requirements.

The process begins with the Input Image Acquisition Module, where users upload medical images such as Brain CT scans, Brain MRI scans, and Chest X-ray images through a web-based interface. These images serve as the input data for the compression framework. The uploaded images are then forwarded to the Classical Preprocessing Module, which performs essential preprocessing operations including image resizing, normalization, noise reduction, and intensity standardization. This stage ensures that all images have a consistent format and quality before being processed by the quantum learning components.

Following preprocessing, the images are passed to the Quantum Encoding and Feature Extraction Module. In this stage, the normalized image data are transformed into quantum states using Parameterized Quantum Circuits (PQCs). The module leverages fundamental quantum computing principles such as superposition, entanglement, and quantum state representation to extract highly informative and compact feature vectors. These quantum-enhanced features capture important structural and textural information while reducing redundancy in the image data.

The extracted feature representations are then processed by the Hybrid QANN Compression Module. This module consists of a quantum-assisted encoder and a classical neural network decoder. The encoder learns compressed latent representations that significantly reduce data dimensionality while retaining critical diagnostic content. The decoder reconstructs the image from the compressed representation, producing a high-quality approximation of the original medical image. This hybrid architecture combines the representational strength of quantum feature learning with the computational efficiency of classical neural networks.

To further improve reconstruction quality, the reconstructed image is passed through the Super Resolution Enhancement Module. This module enhances image sharpness, restores fine anatomical details, reduces compression-induced artifacts, and improves overall visual quality. By recovering high-frequency information lost during compression, the Super Resolution component helps preserve clinically relevant features that are important for medical diagnosis and interpretation.

Finally, the enhanced images are delivered to the Web-Based Visualization Module, which is implemented using the Flask framework. This module provides an interactive user interface that enables users to upload images, perform compression and reconstruction, visualize original and enhanced outputs, compare image quality, and download the processed results. The real-time visualization capability improves usability and supports efficient medical image management.

The modular architecture of the proposed SR-QANN framework ensures effective integration of quantum-enhanced feature extraction, neural network-based compression, and Super Resolution enhancement. As a result, the system achieves high compression efficiency, improved reconstruction quality, and practical real-time performance, making it highly suitable for telemedicine, cloud healthcare platforms, remote diagnostics, and other bandwidth-constrained medical imaging environments.

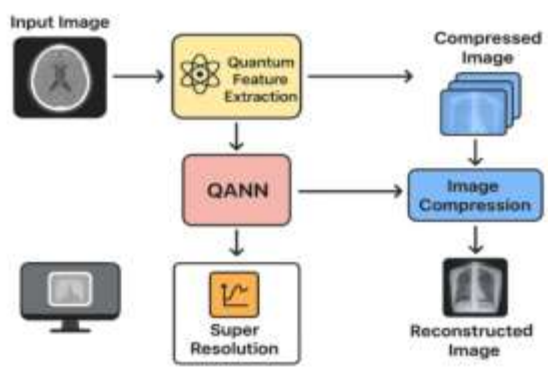

Fig1 proposed architecture

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

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.

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

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.

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

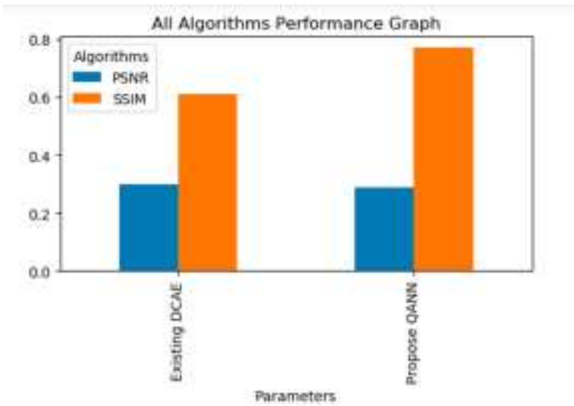

Fig2 Comparision graph

Fig2 Results

Table.1 Performance Evaluation

Algorithm Name	**SSIM**	**PSNR**
Existing DCAE	0.61	0.30
Proposed QANN Model	0.77	0.29

5. CONCLUSION

his work presented a Super Resolution Assisted Quantum-Enhanced Artificial Neural Network (SR-QANN) framework for high-quality medical image compression and reconstruction. The proposed approach combines quantum-enhanced feature extraction with classical neural network-based compression to efficiently reduce image size while preserving critical diagnostic information. By exploiting quantum computing concepts such as superposition and entanglement, the framework generates compact and informative feature representations that improve compression efficiency and minimize information loss.

To address the degradation of fine image details that may occur during compression, a Super Resolution enhancement module was integrated into the reconstruction stage. The enhancement process effectively restores subtle anatomical structures, improves structural similarity, sharpens image features, and reduces compression-related artifacts without introducing significant computational overhead. As a result, the reconstructed images maintain high visual and diagnostic quality, making them suitable for clinical interpretation.

Experimental evaluation demonstrated that the proposed SR-QANN framework achieves superior image reconstruction performance compared to conventional deep convolutional autoencoder-based compression methods. The model consistently preserves image fidelity, maintains high Peak Signal-to-Noise Ratio (PSNR) values, and achieves improved Structural Similarity Index Measure (SSIM) scores, indicating enhanced reconstruction accuracy and structural preservation.

Furthermore, the implementation of the framework as a Flask-based web application enables real-time image upload, compression, reconstruction, and Super Resolution enhancement through an interactive user interface. This practical deployment supports efficient medical image management and facilitates seamless operation in real-world healthcare environments.

Overall, the proposed SR-QANN framework demonstrates that the integration of hybrid quantum–classical learning techniques with Super Resolution enhancement provides an effective solution for next-generation medical image compression systems. The framework offers a balanced combination of compression efficiency, reconstruction quality, and real-time usability, making it highly suitable for telemedicine, remote diagnostics, cloud healthcare platforms, and other bandwidth-constrained medical imaging applications. Future research can further explore advanced quantum architectures and deep Super Resolution models to achieve even higher compression performance and image quality.

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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