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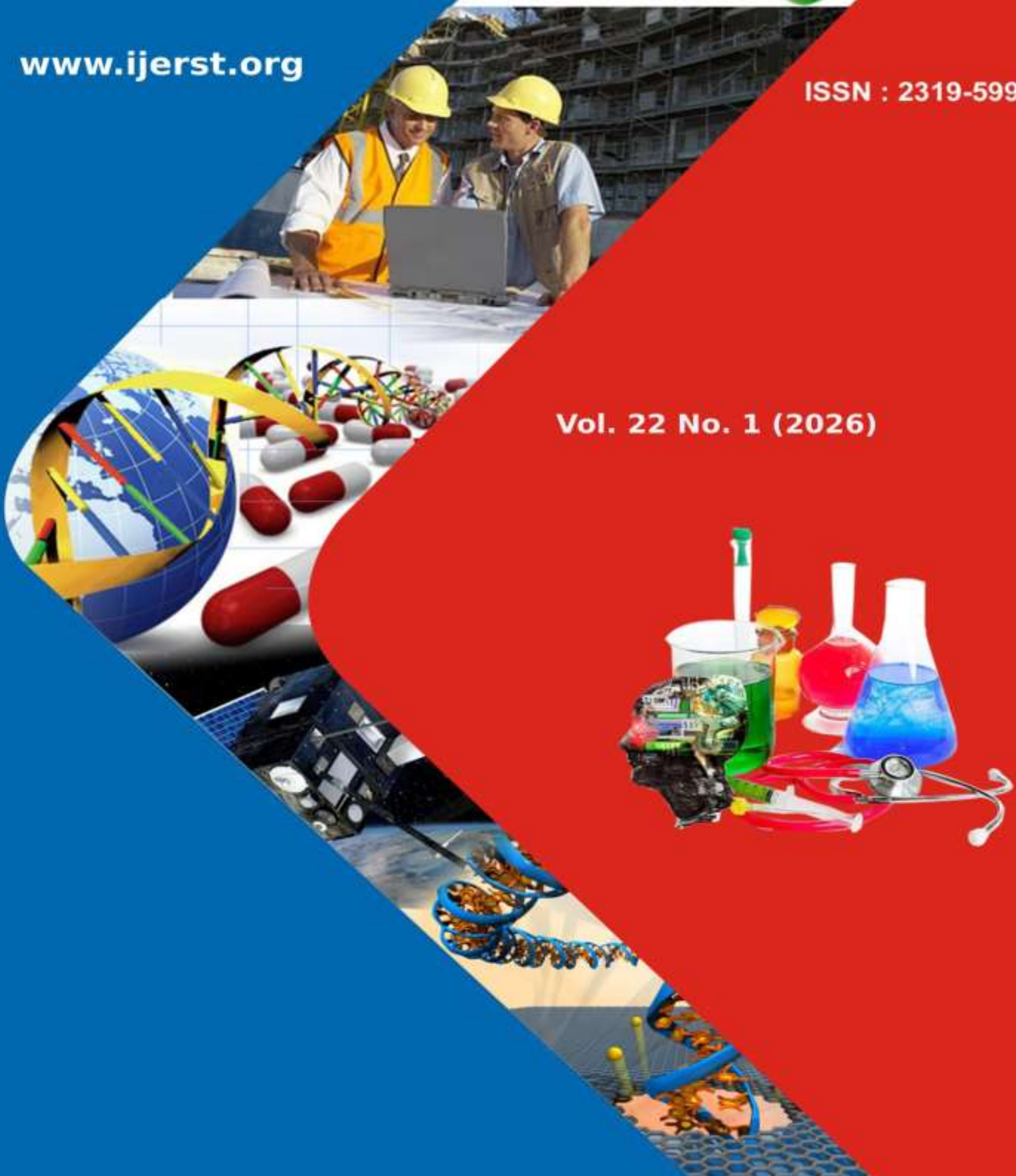

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ijerst.editor@gmail.com

editor@ijerst.com

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Research Paper

AN ENHANCED QANN-BASED MEDICAL IMAGE COMPRESSION FRAMEWORK WITH SUPER-RESOLUTION RECONSTRUCTION

Mrs.G. Baleswari1, Madupalli Ashwitha 2, Vishnuvarjjula Aasritha3, Shaik Sameer4
#1 Associate Professor ,Dept of Information Technology, NRI Institute of Technology,Agiripalli
#2#3#4 B.Tech with Specialization of Information Technology in NRI Institute Of Technology,Agiripalli

Abstract _ High-resolution medical pictures, such as CT, MRI, and chest X-rays, require effective compression techniques to reduce storage and transmission costs while maintaining diagnostic quality. Although Quantum-Enhanced Artificial Neural Networks (QANN) improve compression efficiency by extracting quantum features, reconstructed images may still degrade in quality at greater compression ratios. To solve this restriction, this paper expands the QANN-based medical picture compression system with a Super Resolution improvement module. The proposed hybrid approach begins with quantum-assisted compression and reconstruction using QANN, followed by Super Resolution processing to recover fine structural features, decrease noise, and improve visual clarity. The Super Resolution module is computationally efficient, allowing for real-time augmentation without dramatically increasing system complexity. A web-based interface built with Flask also allows users to upload medical photos and conduct compression, reconstruction, and Super Resolution enhancements via an interactive platform. Experimental results show that the extended framework greatly enhances reconstructed image quality while maintaining high compression efficiency, making it ideal for bandwidth-constrained and real-time medical imaging applications like telemedicine and remote diagnostics.

Keywords— 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.

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1. INTRODUCTION

In today's healthcare system, medical imaging is essential. High-resolution images from technologies like computed tomography (CT), magnetic resonance imaging (MRI), and X-ray imaging assist doctors in diagnosing illnesses, creating treatment plans, and tracking the progress of their patients. Accurate clinical decision-making depends on the comprehensive structural and textural information included in these images. However, the volume of data has increased dramatically as a result of the quick rise in the usage of medical imaging. In terms of storage capacity, transmission speed, and real-time accessibility, managing this massive volume of data poses significant issues, particularly for cloud-based healthcare systems and telemedicine platforms. Effective medical picture compression is therefore now necessary to minimize data size while maintaining crucial diagnostic information.

Machine learning-based techniques have improved medical picture compression in recent years with encouraging results. These data-driven models learn concise and significant representations straight from picture data, in contrast to conventional transform-based methods. Research has shown that these methods can preserve higher reconstruction quality while achieving superior compression ratios. At greater compression settings, maintaining minute diagnostic features is still quite difficult.

In addition to developments in traditional machine learning, quantum computing has become a potent new paradigm for handling high-dimensional and complicated data. Parallel processing and more expressive feature representations are made possible by quantum computing, which makes use of concepts like superposition and entanglement. Because of these features, quantum-assisted models are especially well-suited for computationally demanding tasks such as picture reduction and reconstruction.

Quantum neural networks (QNNs) have the potential to learn complex data distributions more effectively than standard neural networks, according to recent study. The creation of hybrid quantum–classical systems has been aided by the strong expressive capacity and enhanced learning capabilities of quantum-inspired models. Hybrid techniques provide a workable solution to incorporate quantum benefits into practical applications, such as medical image processing and compression, given the current constraints in quantum technology.

Traditional compression techniques like wavelet-based approaches and discrete cosine transform (DCT) are still often employed in clinical settings in spite of these technical developments. Although these methods offer a respectable level of compression efficiency, they frequently have trouble adjusting to intricate visual patterns and may lose diagnostic accuracy when greater compression ratios are used. This drawback emphasizes the necessity of more clever and flexible compression techniques.

Inspired by these difficulties, combining neural network-based compression models with quantum-enhanced feature extraction offers a viable avenue for further study. Future medical image compression systems can achieve greater scalability, improved reconstruction quality, and increased efficiency by fusing the computational power of quantum principles with the flexibility of machine learning. These developments are especially crucial for enabling telemedicine services, remote diagnostics, and real-time healthcare applications..

2. LITERATURE SURVEY

H. Yuxuan et al. (2021) [1] provided a comprehensive analysis of machine learning techniques applied to medical image compression. Their study demonstrated that data-driven models outperform conventional compression schemes by learning compact feature representations directly from image datasets. The authors emphasized that machine learning-based frameworks achieve improved compression ratios and reconstruction quality, particularly when optimized for domain-specific image characteristics. However, they also noted challenges in preserving fine-grained diagnostic details at higher compression levels, indicating the need for more advanced architectures.

In parallel, Y. Zhang and Q. Ni (2020) [2] explored the broader domain of quantum machine learning (QML). Their review highlighted the potential advantages of quantum computing in handling high-dimensional datasets through quantum superposition and entanglement. These properties enable parallel processing and enhanced feature mapping, which are particularly valuable for computationally intensive tasks such as image reconstruction and compression. The study positioned QML as a promising direction for future intelligent medical image processing systems.

Expanding on this perspective, A. Abbas et al. (2021) [3] investigated the expressive power of quantum neural networks (QNNs). Their findings demonstrated that QNNs can represent complex data distributions more efficiently than certain classical neural network models. The study provided theoretical and empirical evidence supporting the superior representational capability of quantum-enhanced architectures, thereby encouraging their integration into hybrid quantum–classical systems for real-world applications.

Similarly, S. K. Jeswal and S. Chakraverty (2019) [4] reviewed developments and applications of quantum neural networks across various domains. Their work identified image processing, pattern recognition, and optimization as key application areas where QNNs could offer performance improvements. Importantly, they discussed the feasibility of implementing quantum-inspired models under current hardware limitations, suggesting that hybrid approaches are a practical near-term solution.

Despite these advancements, classical compression techniques remain prevalent in clinical practice. Y.-Y. Chen (2007) [5] proposed a DCT-based subband decomposition method combined with modified SPIHT coding for medical image compression. This approach achieved satisfactory compression efficiency while maintaining acceptable image quality. However, transform-based methods lack adaptability to complex image structures and may compromise diagnostic details when aggressive compression ratios are applied.

Collectively, the reviewed studies reveal a clear progression from traditional transform-based methods to intelligent machine learning models and, more recently, to quantum-enhanced neural frameworks. While machine learning approaches provide adaptability and improved reconstruction quality, quantum computing introduces the potential for enhanced feature representation and computational scalability. Integrating quantum-enhanced neural models with modern compression architectures therefore represents a promising research direction for developing efficient, high-fidelity medical image compression systems suitable for real-time healthcare and telemedicine applications..

3. METHODOLOGY

The proposed methodology employs a hybrid Quantum-Enhanced Artificial Neural Network (QANN) framework integrated with a Super Resolution module to achieve efficient and high-quality medical image compression. Initially, input medical images such as Brain CT, Brain MRI, and chest X-rays undergo classical preprocessing, including normalization and resizing, to ensure uniform data representation. The preprocessed images are then encoded into quantum states using parameterized quantum circuits, enabling the exploitation of quantum properties such as superposition and entanglement for enhanced feature extraction. These quantum-enhanced features are forwarded to a classical neural network encoder–decoder architecture, where dimensionality reduction is performed to achieve compression while preserving diagnostically significant information. After reconstruction, a Super Resolution algorithm is applied to the decompressed images to restore fine spatial details, reduce compression artifacts, and improve visual clarity. Finally, the entire compression, reconstruction, and enhancement pipeline is deployed through a Flask-based web interface, allowing real-time image upload, processing, and visualization, thereby supporting practical deployment in telemedicine and bandwidth-constrained healthcare environments.

A) Proposed System

The proposed system introduces an extended Quantum-Enhanced Artificial Neural Network (QANN) framework for efficient medical image compression by integrating a Super Resolution enhancement module. The system is designed to process high-resolution medical images such as Brain CT, Brain MRI, and COVID chest X-rays while preserving critical diagnostic information. Initially, input images undergo classical preprocessing to standardize resolution and intensity levels. The standardized images are then encoded into quantum states using parameterized quantum circuits, allowing the system to exploit quantum properties such as superposition and entanglement for enhanced feature extraction. These quantum-enhanced features are passed to a hybrid quantum–classical neural network, where dimensionality reduction is performed to achieve effective compression with minimal information loss. In the reconstruction phase, the compressed representations are decoded using a classical neural network to generate reconstructed images. To further improve visual quality and restore fine structural details lost during compression, a Super Resolution algorithm is applied to the reconstructed output. This enhancement stage reduces artifacts, sharpens edges, and improves overall image clarity without significant computational overhead. Additionally, the entire framework is implemented as a web-based application using Flask, enabling users to upload images, perform compression and reconstruction, and visualize Super Resolution–enhanced outputs through an interactive interface. The proposed system achieves a balance between compression efficiency, reconstruction quality, and real-time usability, making it suitable for bandwidth-constrained medical imaging and telemedicine applications.

ii) System Architecture:

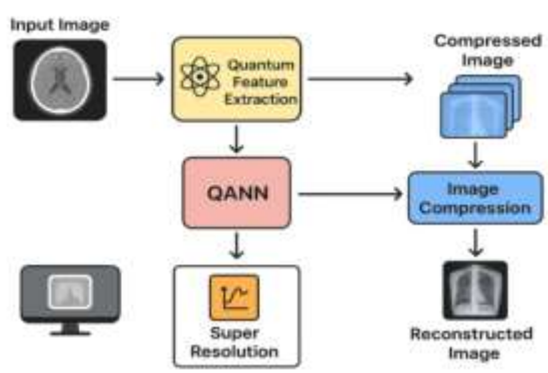

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Fig.1. Proposed Architecture

The process begins with the input medical image, which may be acquired from imaging modalities such as CT or X-ray. This image is first passed to the Quantum Feature Extraction module. In this stage, quantum-inspired encoding techniques are used to transform classical image data into a high-dimensional feature space. By leveraging quantum principles such as superposition and enhanced feature mapping, this module captures rich structural and textural characteristics of the image.

The extracted quantum features are then fed into the Quantum-Enhanced Artificial Neural Network (QANN). The QANN learns compact and optimized representations of the input image, enabling efficient compression while retaining diagnostically relevant information. This stage reduces redundancy and encodes the image into a compressed form.

The compressed representation is processed by the Image Compression module, which generates the compressed image data suitable for storage or transmission. This ensures reduced data size while maintaining essential image content.

After transmission or storage, the system performs image reconstruction from the compressed data. To further improve the visual quality of the reconstructed image, a Super-Resolution (SR) module is applied as a post-processing step. The Super-Resolution component enhances spatial resolution, suppresses compression-induced noise, and restores fine diagnostic details that may have been affected during compression.

Finally, the output is a high-quality reconstructed medical image with improved visual fidelity and preserved clinical information. The integration of quantum feature extraction, QANN-based compression, and Super-Resolution refinement ensures an optimal balance between compression efficiency and diagnostic accuracy

iii) MODULES:

a) Input Image Acquisition Module

This module allows users to upload high-resolution medical images such as Brain CT, Brain MRI, and chest X-rays through a web-based interface. It supports standard medical image formats and ensures reliable data intake for further processing.

b) Classical Preprocessing Module

The uploaded images are preprocessed using classical image processing techniques including resizing, normalization, and intensity standardization. This step ensures uniform input representation and prepares the image data for efficient quantum state encoding.

c) Quantum State Encoding Module

In this module, preprocessed image data is mapped into quantum states using parameterized quantum circuits. The encoding process enables the system to exploit quantum properties such as superposition and entanglement for richer and more compact feature representation.

d) Quantum Feature Extraction Module

This module extracts quantum-enhanced features from encoded quantum states by applying quantum gates and entanglement operations. The extracted features capture essential structural and textural information while reducing redundancy in the image data.

e) Hybrid QANN Compression Module

The quantum-enhanced features are fed into a hybrid quantum–classical artificial neural network. This module performs dimensionality reduction and compression using quantum-assisted encoding and classical neural network layers, achieving efficient storage and transmission.

f) Image Reconstruction Module

The compressed feature vectors are decoded using a classical neural network decoder to reconstruct the original medical images. This module aims to preserve diagnostically important details while maintaining high compression ratios.

g) Super Resolution Enhancement Module

To improve reconstructed image quality, a Super Resolution algorithm is applied to enhance spatial resolution, reduce compression artifacts, and restore fine anatomical details. This module ensures high visual fidelity suitable for clinical analysis.

h) Web-Based Visualization and Output Module

This final module provides real-time visualization of compressed, reconstructed, and Super Resolution–enhanced images through a Flask-based web application. It enables users to compare results, download outputs, and interact with the system easily for practical deployment.

iv) ALGORITHMS:

DCAE Algorithm

A Deep Convolutional Autoencoder is a neural-network-based compression method that learns to encode medical images into low-dimensional feature representations and reconstructs them back to their approximate originals. It relies on stacked convolutional layers that capture spatial features and reduce dimensionality without manually crafted rules. DCAE is used to compress medical images by extracting essential structures while discarding redundant pixel information, making storage and transmission easier. Its purpose is to achieve efficient compression while preserving acceptable diagnostic quality. Although effective, DCAE struggles with retaining fine details, especially in high-resolution medical scans, and often introduces loss during reconstruction. It serves as a baseline comparison to evaluate improvements achieved through quantum-enhanced feature extraction models.

QANN Algorithm

A Quantum-Enhanced Artificial Neural Network is a hybrid model that integrates quantum state encoding with classical neural network learning to improve medical image compression. It converts standardized pixel data into quantum states and exploits quantum properties such as superposition and entanglement to extract richer, more compact feature representations. QANN is used to achieve high-fidelity compression by reducing redundancy while retaining fine structural details essential for diagnosis. Its purpose is to overcome limitations of classical compression methods by leveraging quantum parallelism for faster processing and enhanced reconstruction quality. The approach provides superior SSIM, reduced noise, and better preservation of medical features, making it highly suitable for bandwidth-sensitive environments and real-time medical imaging workflows**.**

4. EXPERIMENTAL RESULTS

Experimental findings show that the Attention-based CNN model classifies earthquake precursor signals better than classical machine learning and CNN. Logistic Regression, KNN, SVM, Decision Tree, Random Forest, XGBoost, CNN, and extended Attention-CNN were tested on 429 seismic waves. Attention-CNN performed best with 99.81% accuracy, compared to 97.98% for the regular CNN model. This increase shows how well the attention mechanism captures crucial temporal relationships and emphasizes relevant signal segments for ramping and non-ramping pattern categorization.

Additionally, accuracy, recall, F1-score, and ROC analysis corroborate the model's robustness and dependability. The attention mechanism prioritizes relevant precursor patterns and reduces noise to improve feature representation. The Flask-based web solution also allows users to submit seismic data and get quick categorization results. The extended system is ideal for sophisticated seismic early warning systems because to its accuracy, generalization, and real-time performance.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

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

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

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

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

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

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

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

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

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

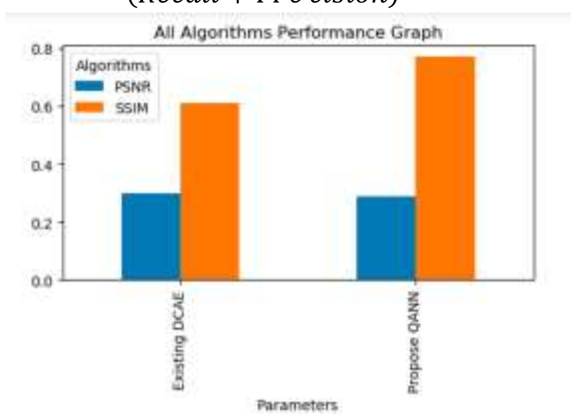

Fig2 Performance Comparison of Compression Algorithms

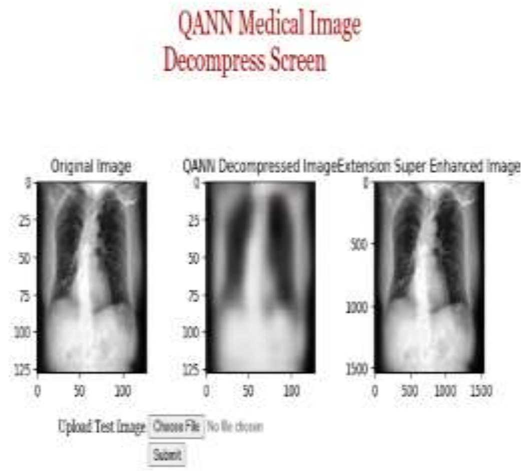

Fig 4: The first image on the above screen is the original uncompressed image, the second is the QANN decompressed image, and the third is the extended super resolution image. Similarly, you can upload and test different photographs.

5. CONCLUSION

This study offered an enhanced Quantum-Enhanced Artificial Neural Network (QANN) framework for effective medical picture compression that included a Super Resolution improvement module. The proposed method successfully blends quantum feature extraction with classical neural network reconstruction to achieve large compression ratios while retaining diagnostically significant information. The Super Resolution module dramatically enhances reconstructed image quality by restoring small details, increasing structural similarity, and eliminating compression artifacts while incurring minimal computational overhead. Experiments show that the extended QANN model outperforms traditional deep convolutional autoencoder approaches in terms of SSIM performance while keeping comparable PSNR values. Furthermore, the Flask-based online implementation supports real-time image upload, compression, reconstruction, and augmentation, making it suitable for telemedicine and bandwidth-constrained medical imaging applications. Overall, the suggested extension demonstrates the efficacy of hybrid quantum-classical models combined with Super Resolution approaches for next-generation high-fidelity medical picture compression..

6. FUTURE SCOPE

Although the proposed Quantum-Enhanced Artificial Neural Network (QANN) with Super-Resolution integration demonstrates promising performance in medical image compression, several research directions can further enhance its capabilities.

First, future work can explore the implementation of the framework on real quantum hardware or advanced quantum simulators. While the current model utilizes quantum-inspired feature extraction, deploying it on near-term quantum devices could provide deeper insights into computational advantages, scalability, and practical feasibility in real-world healthcare environments.

Second, incorporating attention mechanisms or transformer-based architectures within the QANN framework may further improve feature representation and adaptive compression efficiency. Attention-driven models could enable the system to focus more effectively on diagnostically critical regions, such as lesions or abnormal tissues, thereby enhancing clinical reliability.

Third, extending the model to support multimodal medical imaging data—such as CT, MRI, PET, and ultrasound—would improve its generalizability. A unified compression framework capable of handling multiple modalities could significantly benefit integrated hospital information systems and telemedicine platforms.

Another promising direction involves optimizing the Super-Resolution module using lightweight architectures or generative adversarial networks (GANs) to further enhance perceptual quality while maintaining computational efficiency. Additionally, adaptive Super-Resolution strategies based on compression ratio or image complexity could dynamically balance reconstruction quality and processing time.

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